Style investing: International evidence

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STYLE INVESTING: INTERNATIONAL EVIDENCE

A Dissertation

by

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ABSTRACT

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This dissertation studies the impact of investor sentiment on a portfolio formed of sin stocks—publicly traded companies in the alcohol, tobacco, and gaming industries. It also investigates the returns of a new type of sin stock in the UK—online gambling. Chapter 3 first uses a vector autogressive model to study the impact of both rational and irrational investor sentiments on *pure* sin returns. Next, making use of a variety of sentiments-augmented asset pricing models, this research examines whether investor sentiment is a risk factor for sin stock returns and if the abnormal returns of sin stocks persist after controlling for investor sentiment. Finally, the possible relationship between investor sentiment and the conditional volatility of the sin portfolio is studied by utilizing a generalized autoregressive conditional heteroscedasticity-in-mean model. The results indicate that rational-based sentiments shocks illicit a larger positive response in pure sin returns, than do irrational-based sentiments shocks. After controlling for the role of investor sentiment, the asset-pricing results suggest that the abnormal returns for sin stocks found in previous studies disappear. Furthermore, findings show that both individual and institutional investor sentiment are priced factors in sin stock returns. Additionally, results indicate that investor sentiment has a significant impact on sin stocks' formation of volatility.

Chapter 4 of this dissertation examines the financial performance, time-varying betas, and time-varying correlations of an internet gambling portfolio relative to both the market and socially responsible portfolios. Findings indicate that the online gambling portfolio underperforms relative to both the market and socially responsible portfolios. The evidence also suggests that beta is time-varying for the online gambling portfolio. Furthermore, market betas and correlations for the online gambling portfolio increase considerably around the passage of the Gambling Act 2005.

DEDICATION

I dedicate this dissertation to my family, especially to my wife and daughter—Zuri and Ainoa. Thank you for always being there and for helping make this dream a reality. To my parents, Judith and Jose Manuel, who taught me that anything is possible and that knowledge is the key to a better future. To my brothers, Travis and Robert, as your youngest brother, I have learned a great deal from both of you. To my grandmother, Sara, thank you for believing in me. To my in-laws, I want to thank you for your support and patience. To the rest of my family, thank you for your love and support.

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CHAPTER I

INTRODUCTION

Sin stocks may be defined as shares of publicly traded companies whose main business activities include alcohol, tobacco, and gambling. The academic literature for sin stocks is in its nascent state. The small but growing literature documents large risk-adjusted returns for portfolios formed of sin stocks (Hong and Kacperczyk, 2009; Fabozzi, MA, and Oliphant, 2008; Salaber, 2007a). Return premiums presumably arise due to a lack of risk sharing, where sin investors are rewarded for holding more shares than they otherwise would. However, a major limitation of these studies is that they ignore the possible relation between investor sentiment and sin stock returns. Evidence suggests that individual investor sentiment might influence sin stock returns because sin stocks are less held by institutional investors (Hong and Kacperczyk, 2009; Kim and Venkatachalam, 2008). Additionally, these studies also suggest that social norms—non-financial attributes—might play a role in the return generating process for sin stocks. Therefore, this dissertation considers whether waves of both individual and institutional investor sentiment influence sin stock returns and volatility.

In recent years, the World Wide Web has revolutionized the way in which games of chance are played. The rapid emergence of online gambling—using the internet to play a game of chance for stakes—stresses the need for academic scrutiny of publicly listed online gambling companies. However, due to the newness of this narrow form of sin stock, very little academic research has been conducted across all academic disciplines. For example, in finance, academic literature that investigates online gambling companies and their financial returns is virtually nonexistent.[1] Therefore, many questions remain unanswered for online gambling stocks. For instance, the literature remains silent on the degree to which online gambling stocks co-vary with the market portfolio and does not quantify systematic risk (beta) for a portfolio formed of online gambling stocks. In addition, the financial performance for online gambling stocks relative to the market and to its antagonist—socially responsible investing—has yet to be examined. Finally, the literature has not studied the impact of the passage of the Gambling Act 2005 on the betas and correlations for online gambling stocks.

The next chapter of this dissertation reviews the academic literature for sin stocks, investor sentiment, and online gambling stocks. Each topic begins with its definition and discussion of background where applicable, followed by a discussion of the relevant literature from an empirical and theoretical perspective.

Chapter 3 examines the relation between a portfolio formed of sin stocks and investor sentiment. First, unlike the existing literature, sin returns are dichotomized into a market-based component and a pure sin component. Furthermore, both individual and institutional investor sentiments are split up into rational and irrational components. Second, the dynamic link

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[1] The author has only identified one published article in the field of finance.

between investor sentiment and *pure sin* returns using a vector autoregressive model is investigated. Third, determine whether individual (institutional) investor sentiment influences pure sin returns through the irrational or rational component of sentiment. Fourth, using a generalized autoregressive conditional heteroskedastic model, this dissertation tests whether the conditional volatility of the sin portfolio clusters over time. Fifth, this study examines if bad news has a larger impact on sin stock volatility than good news. Sixth, we test if sin stock returns depend on its volatility. Seventh, the volatility analysis is extended by studying the impact of investor sentiment on the formation of volatility for the sin portfolio. Lastly, sentiments-augmented asset pricing models are used to investigate whether behavioral risk factors can account for the over performance found in previous empirical studies.

Impulse response functions from the vector autoregressive models show that both individual and institutional rational-based sentiment shocks positively influence pure sin returns. However, irrational-based shocks have a positive but insignificant effect on pure sin returns. The results from the GARCH model indicate that investor sentiment has a positive impact on the excess returns of the sin portfolio. The evidence also suggests volatility clustering and a leverage effect for sin stocks. Moreover, the results show that sin stock returns are positively related to its volatility, but only when individual sentiment is included in the model. Furthermore, noise trader risk influences the formation of volatility for the sin portfolio; however, the direction of this impact depends on whether individual or institutional investor sentiment is used. In an asset-pricing framework, this study finds evidence that both irrational individual and institutional investor sentiments positively influence sin returns. Furthermore, after adjusting for a four-factor model, the results show that a portfolio of sin stocks generates a 62-basis point premium per month. However, the premium disappears after controlling for the role of both individual and institutional investor sentiment. This suggests that the large returns for sin stocks might be due to sentiment risk. In general, the results support fundamentals-based arguments for sin returns, but they also favor the view that investor error is a significant determinant of sin stock returns and volatility.

Chapter 4 examines a new trend in gambling—online gambling. This chapter first contributes to the literature by examining the financial performance of an online gaming portfolio and then comparing it to both the market and socially responsible portfolios. Second, this study quantifies beta for the online gambling portfolio and investigates whether it is time-varying. Third, we examine dynamic correlations between the market and online gambling portfolios. Finally, this dissertation documents the effect of UK gambling legislation on the conditional betas and correlations of the online gambling portfolio.

Chapter 4 yields several results. First, unconditional and conditional financial performance measures indicate that the online gambling portfolio underperforms the market and the socially responsible portfolios. This result contrasts the findings of Chapter 3, which finds that sin stocks outperform the market. Second, the beta for the online gambling portfolio is less than one, indicative of defensiveness towards the market, a result which collaborates with that found in Chapter 3 for sin stocks. Third, the conditional correlation between the market and online gambling portfolio is small when compared to the correlation of the market and the socially responsible portfolio. Finally, findings suggest that the Gaming Act 2005 increases the conditional correlation between the market and online gambling portfolio and it also increases the conditional betas for the online gambling portfolio.

The results of this dissertation suggest that the return generating process for a portfolio of sin is affected by both fundamental and non-fundamental factors (i.e., investor sentiment). This dissertation finds common and distinct features in the returns of the sin and online gambling portfolios. The sin portfolio is similar to the online portfolio in that both tend to have betas less than one and their betas move inversely to the betas of socially responsible portfolios. Furthermore, both portfolios exhibit relatively high standard deviations and both tend to exhibit volatility clustering. However, they are different in that the sin portfolio has large mean returns, whereas the online gambling portfolio has relatively low mean returns. Also, the risk-adjusted measures indicate that the online gambling portfolio underperforms, whereas the sin portfolio over performs.

CHAPTER II

LITERATURE REVIEW

What are sin stocks? What is online gambling? What is individual and institutional investor sentiment? This chapter presents a summary of what is known and is not known about each of these topics. In Section 2.1, I provide an overview of sin stocks. The overview begins by defining sin stocks and then provides a brief background for these stocks. After that, I review the extant empirical literature for sin stocks and discuss some theoretical models related to such stocks. In Section 2.2, I first begin by defining investor sentiment, and then proceed to discuss some important empirical and theoretical papers for this literature. Finally, Section 2.3 examines the definition of online gambling, followed by recent global and legislative trends for these stocks. The section concludes by presenting some empirical research for online gambling.

2.1 An Overview of Sin Stocks

2.1.1 Sin Stocks: Definition

There is no exact definition of what constitutes a sin portfolio. The majority of the sin literature forms the sin portfolio by including stocks from the alcohol, tobacco, and gaming industries (Hong and Kacperczyk, 2009; Visaltanachoti, Zou, and Zheng, 2009; Salaber, 2007a; Salaber, 2007b). Collectively these stocks are sometimes referred to as the Triumvirate of Sin.

An important reason for including tobacco, alcohol, and gaming in the sin portfolio is because they are the most well know exclusionary criteria for socially responsible investing. Screens do share some common themes. According to The Social Investment Forum (1998), more than 80 percent of socially screened portfolios exclude tobacco, over 70 percent exclude gambling, and in excess of 60 percent exclude alcohol. Furthermore, the following socially responsible indices all exclude alcohol, tobacco, and gambling companies from their index composition; FTSE4Good, Domini 400, and KLD Select Social. Moreover, addiction is a common theme across these three sin industries. For example, Salaber (2007a) points out that these three types of industries sell products to consumers that have addictive behavior. While the definition of sin stocks in this dissertation focuses on the Triumvirate of Sin, there are two other industries that society sometimes considers as sinful but are excluded from our analysis. The first is the defense industry. In our investigation we leave out the defense industry since many Americans might not consider defending The United States as sinful behavior. The second is the sex industry. This industry is clearly considered sinful by many; however, we exclude it due to the lack of publicly traded companies.[2]

Other studies have used broader definitions for sin stocks. For example, Olsson (2005) forms the sin portfolio by including the tobacco, alcohol, defense, and gambling industries. However, his results do not change qualitatively when he excludes the defense industry from his empirical analyses. Fabozzi, Ma, and Oliphant (2008) form the sin portfolio by including the adult services, alcohol, biotech, defense, gaming, and alcohol industries. Kim and Venkatachalam (2008) examine the performance of a sin portfolio comprised of the alcohol,

[2] I have only identified two of such publicly traded companies; Private Media Group and Playboy Entertainment.

tobacco, gaming, and sex industries. Lobe and Roithmeier (2008) compose a worldwide index of sin by including the alcohol, gambling, tobacco, sex, arms, and nuclear power industries. Chong, Her, and Phillips (2006) simply use the Vice Fund (VICEX) as a proxy for the sin portfolio.

2.1.2 Background on Sin Stocks

Around the world and in the United States, the alcohol, gambling, and tobacco industries are viewed by many people as producers of products and services that have negative consequences on individuals and society as a whole. As a result, many investors are unwilling or unable to invest in these industries.

Alcohol use is known to adversely affect the physical and mental condition of individuals, as well as having negative consequences for society (Hall et al., 1992).[3] For example, various diseases are fully attributable to alcohol consumption (e.g., alcoholic liver cirrhosis, alcoholic psychoses, and alcohol-dependence syndrome). At the societal level, alcohol consumption can lead to increased traffic accidents, workplace-related problems, family and domestic problems, and interpersonal violence. A study by Rehm et al. (2003) finds that 3.2% of global deaths can be attributed to the exposure of alcohol. Alcohol, therefore, is considered a vice by many governments, individuals, and public (private) institutions.

Similar to alcohol, gambling is also considered harmful to individuals and society. Many studies have set out to quantify problem and pathological gambling prevalence rates. For example, a study by Shaffer et al. (1999) shows that disordered gambling has increased significantly between 1974 and 1997. These kinds of studies have helped contribute to a greater

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[3]For more information of the negative consequences on individuals and society, as a whole, see the World Health Organization's Global Status Report on Alcohol of 2004 (WHO, 2004).

negative perception by the public towards the gambling industry. Despite the adverse effects of gambling on parts of the population, since the 1990s, there has been a move towards greater deregulation of the gambling industry in the United States. According to a report by the National Gambling Commission, by 1999 more than twenty-five states had moved to legalize some form of gambling. The deregulation of gambling suggests that games of chance have become more acceptable to society. However, this does not mean that gambling is seen as promoting social well-being.

Tobacco, like alcohol and gambling, is considered a vice by society. However, this was not always true. Before the mid-twentieth century, society was unaware of the health dangers associated with tobacco. In the 1950s, the first published study linking lung cancer to smoking appeared in the *Journal of the American Medical Association*. The seminal work by Levin, Goldstein, and Gerhardt laid the foundation for the change in public opinion towards tobacco products. Today, few in society doubt the link between tobacco related products and the various types of cancers these cause.

2.1.3 Empirical Findings for Sin Stocks

The empirical literature has produced some interesting findings for sin stocks in the past decade. For example, Olsson (2005) examines the financial performance and risk-return characteristics of an unethical investment strategy. After controlling for various well-know predictors of stock returns, he finds that sin stocks over performed from 1985 to 2004 and behaved like value stocks. In addition, he documents evidence of time-variations in social norms using the tobacco lawsuit settlement of 1997. Chong, Her, and Phillips (2006) studied the risk and performance of the Vice Fund—a fund which invests only in sin stocks. Using unconditional and conditional performance measures they show that the Vice Fund outperformed the market from 2002 to 2005. Salaber (2007a) examines whether the over performance of sin stocks changes over the business cycle. She finds that the abnormal returns on the sin portfolio are higher during recessions than expansions. When examined by industries, the tobacco and alcohol industries exhibit similar returns patters over the business cycle, whereas gaming stocks respond distinctly.

Salaber (2007b) examined whether the legal and cultural characteristics of 18 European countries influence sin stock returns. Using monthly data from 1975 to 2006, she compares sin returns in European countries where the largest fraction of the population practices either Protestantism or Catholicism. She finds that abnormal returns in Protestant countries are larger than in Catholic countries, which indicates that Protestant countries require a premium on sin stocks. Her results suggest that Protestants are more intolerant to sin investing. Kim and Venkatachalam (2008) investigated if higher information risk (due to poor financial reporting quality) causes the abnormal returns found in sin stocks. Using data from 1988 to 2003 they find that sin firms exhibit superior financial reporting, when compared to a control group, quality in terms of earnings and accrual persistence, predictability of earnings for future cash flows, and timely loss recognition. Thus despite the superior financial reporting quality and higher returns offered by sin stocks, some investors are willing to neglect these stocks due to social pressure. Lobe and Roithmeier (2008) study whether socially responsible investing is a superior financial investment strategy compared to sin investing. Using data from July 1995 to July 2007, their evidence suggests that the risk-return characteristics for sin stocks across the globe are superior to socially responsible stocks as well as regular stocks. Fabozzi, MA, and Oliphant (2008) study excess returns for a sample of 21 mostly developed countries from January 1970 to June 2007, they find that sin stocks exhibit statistically significant excess returns in most of the countries they examined. Their results suggest that the over performance of sin stocks is not just a U.S. phenomena. However, compared to the other countries in the sample, the U.S. exhibited the largest excess returns.

Hong and Kacperczyk (2009) examine the effects of social norms on markets by studying sin stocks. They argue that a societal norm against funding sin firms causes prices to be depressed, thus leading to higher expected returns. They find that sin stocks, on average, outperform a group of comparable stocks even after accounting for well know predictors of stocks returns. Visaltanachoti, Zou, and Zheng (2009) use monthly returns data from January 1995 to March 2008 to study the financial and operating performances of sin stocks for the Asian stock markets. They find that sin stocks outperformed, in terms of financial performance, the market index in both Hong Kong and Mainland China. However, the operating performance of sin stocks was indifferent to other non-sin companies, suggesting that the unique financial performance of sin stocks is not due to differences operating activities.

A major limitation of these studies is that they do not shed light on the possible relation between investor sentiment and sin stock returns. Furthermore, the literature has not examined the volatility for these types of stocks. Previous empirical literature finds that sin stocks are less held by institutional investors and that social norms—non-financial attributes—might play a role in sin stock returns (Hong and Kacperczyk, 2009; Kim and Venkatachalam, 2008). These findings suggest that the returns and volatility for sin stocks might be susceptible to waves of both individual and institutional investor sentiment. Historically, extant literature conducts its empirical analyses through the prism of neoclassical finance. In this dissertation, we argue that a behavioral approach, which accounts for the role of investor sentiment, is a more suitable paradigm when examining sin stocks.

2.1.4 Theoretical Models Related to Sin Stocks

This section discusses two models currently used to explain the observed return behavior for sin stocks; in particular, the observed high-risk adjusted returns for these stocks. The first is based on the assumption that investors differ in their willingness to hold undesirable stocks, while the second assumes that investors have incomplete information regarding the universe of securities.

Heinkel, Kraus, and Zechner (2001), referred to as HKZ hereafter, develop a model where exclusionary ethical investing causes “polluting firms” to be held by fewer investors because “green investors” are unwilling to hold them. Consequently, the lack of risk sharing among all investors leads to higher returns for polluting firms in order to compensate the “neutral investors” that *do* hold shares in polluting firms. The HKZ model is developed in a one-period world. In this economy, the total number of investors I, consists of I_n neutral investors and I_g green investors. Green investors decline to hold the shares of firms that harm the environment, whereas neutral investors are indifferent. That is, investors differ in their acceptance of environmental damage that firms cause. The HKZ model assumes only three types of firms: acceptable firms (A), which satisfy green investors’ screening criteria; unacceptable firms (U), which do not satisfy green investors’ screening criteria; and reformed firms (R), which previously did not satisfy the criteria, but that now do. The total number of firms in this world, N, is composed of N_A acceptable firms, N_U unacceptable firms, and N_R reformed firms. The number of clean firms is equal to the number of acceptable firms ($N_C = N_A$). Also, the number of polluting firms is equal to the sum of the unacceptable firms and the reformed firms ($N_P = N_U + N_R$).

The equilibrium share price for unacceptable firms derived in the HKZ model is as follows:

$$P_U = \mu_P - \frac{1}{I\tau}[N_C\sigma_{CP} + N_U\sigma_P^2 \quad + N_U\frac{I_g}{I_n}\frac{\varphi}{\sigma_C^2} + N_R\frac{\sigma_{CP}^2}{\sigma_C^2}], \tag{2.1}$$

where P_U is the price per share for the unacceptable firm, μ_P is the mean cash flow that polluting firms generate, τ the risk tolerance parameter, N_C the number of clean firms, σ_{CP} the covariance between the cash flows of clean and polluting firms, σ_P^2 variance of the cash flow for polluting firms, σ_C^2 the variance of the cash flow for the clean firms, and $\varphi = \sigma_C^2\sigma_P^2 - \sigma_{CP}^2$.

Using comparative statics, HKZ show that “For a fixed number of investors, more green investors means fewer neutral investors, which in turn means a lower price for unacceptable firms” (p. 439). Thus, lower prices lead to higher expected returns. HKZ also show that “Holding the total number of investors constant, more green investors means that there are fewer neutral investors who are willing to hold unacceptable firms’ shares” (p. 438).

The HKZ model generates premiums for undesirable companies only if there is a large enough proportion of investors that is unwilling to hold these stocks. There is evidence suggesting that more than 10% of investments in the U.S. are in socially responsible investing (SRI) (Hamilton, Jo, and Statman, 1993; Geczy, Stambaugh, and Levin, 2003). Typical SRI screens include alcohol, tobacco, and gambling, thus SRI funds do not invest in these kinds of companies. These studies suggest that the effect of exclusionary ethical investing on sin stocks might be of a reasonable size.

The HKZ model fits well with sin stocks. In the sin stock context, sin firms are the polluting firms; however, here sin firms produce sin instead of pollution. The main theme is that a subset of the entire investor base is unwilling to hold sin stocks. This subset of investors eschews sin stocks because they do not want to infringe social norms. The HKZ model predicts that sins stocks should exhibit high-risk adjusted returns. These risk adjusted returns may be detected by estimating the capital asset pricing model (CAPM). If the HKZ model is correct, then the estimation of the CAPM should lead to a positive and significant Jensen's alpha (Heinkel et al., 2001). Consistent with the HKZ model, Hong and Kacperczyk (2009) estimate the CAPM for a portfolio of sin and find that sin returns are abnormally high. Furthermore, they find that sin stocks they are less held by norm-constrained investors. Their results, however, fail to account for the possible role of investor sentiment on sin stocks returns.

Merton (1987) develops a model of capital market equilibrium with incomplete information. In Merton's model only a subset of the total investor base has information regarding a particular firm. The lack of complete information causes firms' returns to deviate from the security market line. However, with complete information Merton's model reduces to the CAPM. According to Merton (1987), in equilibrium "…less well-known stocks of firms with smaller investor bases tend to have relatively larger expected returns than in the comparable complete-information model" (p.507).

Equation 21 of Merton's paper illustrates the premium associated with incomplete information. The premium is as follows:

$$\bar{R}_k - \bar{R}_k^*, \tag{2.2}$$

where $\bar{R}_k$ is the return on firm *k* with incomplete information and $\bar{R}_k^*$ is the return on firm *k* with complete information. Thus, there is a premium on stocks that investors know little about; the less information available on the stock, the greater the premium.

Consistent with the Merton (1987) model, Hong and Kacperczyk (2009) find that sin stocks receive less analyst coverage, compared to a control group. Less analyst coverage implies less information on sin stocks, which implies that the observed high risk-adjusted returns for sin stocks might be due to incomplete information. In addition, and in contrast to the CAPM, Merton shows that the equilibrium expected return $\bar{R}_k$ for firm *k* is a function of idiosyncratic risk and not just systematic risk. Therefore, the Merton (1987) model predicts that the litigation risk of the alcohol, tobacco, and gambling industries might also play a role in the return generating process for sin stocks.

Taken together, both models (Heinkel, Kraus, and Zechner, 2001; Merton, 1987) predict that sin stocks should exhibit positive abnormal returns.

2.2 An Overview of Investor Sentiment

2.2.1 Investor Sentiment: Definition

"Noise causes markets to be somewhat inefficient, but often prevents us from taking advantage of inefficiencies."

Fisher Black, 1986

"Noise"

The Journal of Finance, Volume 41, pp. 529-543.

Investor sentiment is an ambiguous construct and as a result researchers define it in various ways. In finance, sentiment is usually synonymous with investor error (Shefrin, 2005). For example, Zweig (1973) defines investor sentiment as the one-sided (biased) expectations of non-professional investors. According to Black (1986), investor error arises from noise (pseudo-signals). De Long et al. (1990) explicitly model investor sentiment as noise traders' mean misperception of security prices. Baker and Wurgler (2007) define investor sentiment as, "…a belief about future cash flows and investment risks that is not justified by the facts at hand" (p.129).

Shefrin (2005) offers a formal definition of sentiment. He defines sentiment as:

$$\Lambda = \ln\left(\frac{P_R}{\Pi}\right) + \ln\left(\frac{\delta_R}{\delta_{R,\Pi}}\right), \tag{2.3}$$

where Λ is the sentiment function, P_R the representative investor's probability density function, Π the objective probability density function, δ_R is the equilibrium time discount factor for the representative investor, and $\delta_{R,\Pi}$ is the objectively correct time discount factor. He defines sentiment in terms of probability distributions as investor error is not only limited to the first moment of a distribution, as it can be observed in the second, third, and fourth moments of a return distribution.

2.2.2 Empirical Findings for Investor Sentiment

"In the muddled days before the rise of modern finance, some otherwise reputable economists, such as Adam Smith, Irving Fisher, John Maynard Keynes, and Harry Markowitz, thought that individual psychology affects prices."

David Hirshleifer, 2001

"Investor Psychology and Asset Pricing"

The Journal of Finance, Volume 56, 1533-1597

Often, economists argue that investor errors are independent across individuals canceling out in equilibrium. However, this view ignores the fact that individuals share common rules of thumb (heuristics). As a result, heuristics introduce systematic biases in individual decision making, which might be reflected in market outcomes (Hirshleifer, 2001). Rashes (2001) provide a good example of the impact noise traders may have on stock prices in the context of co-movements between two stocks having similar ticker symbols. For example, Rashes compares MCI with MCIC. However, MCI is the ticker symbol for MassMutual Corporate Investors, a closed-end fund listed NYSE and MCIC is the ticker symbol of MCI Communications, a large telecommunications company. Both companies are in completely different industries, thus future cash flows are likely to be unrelated. In his study, Rashes reports that noise traders often confuse the two ticker symbols, thereby driving the price of the telecommunications company away from the fundamental value for short periods of time.

Various studies have examined the impact of investor sentiment on stock returns using indirect measures of investor sentiment: market-performance based measures (Brown and Cliff, 2004); trading activity-based measures (Neal and Wheatley, 1998; Brown and Cliff, 2004); derivative variables (Brown and Cliff, 2004); close-end fund discount (Lee et al., 1991; Chan et al., 1993; Swaminathan, 1996; Elton et al., 1998; Neal and Wheatley, 1998; Sias et al., 2001; Gemmill and Thomas, 2002; Baker and Wurgler, 2006); dividend premium (Baker and Wurgler, 2006) and IPOs-related measures (Baker and Wurgler, 2006; Brown and Cliff, 2004). In general, these studies report mixed results between sentiment and stock returns, perhaps due to the indirect nature of such measurements.

Studies relating individual investor sentiment to stock returns find that direct measures of sentiment are strongly correlated with stock returns (De Bondt, 1993; Brown and Cliff, 2004). Studies which examine the impact of institutional sentiment on stock prices find that sentiment is contemporaneously correlated with excess returns (Solt and Statman, 1988; Clarke and Statman, 1998; Lee et al., 2002; Brown and Cliff, 2004). Verma et al. (2008) distinguish between sentiments-induced fundamental trading and sentiments-induced noise trading and find that the impact of rational sentiments is larger than that of irrational sentiments with respect to the S&P 500. Their empirical evidence favors suggests that investor error affects both the Dow Jones Industrial Average and the Standard & Poor's markets. Overall, the aforementioned studies provide evidence of institutional and individual sentiments' influence on asset prices. Chapter 3 of this dissertation follows this literature and examines the relation between investor sentiment and sin stock returns using direct measures of individual and institutional investor sentiment.

2.2.3 Theoretical Models on Investor Sentiment

Black (1986) develops a model where *noise*[4] has an effect on financial markets. He argues that noise in financial markets may cause prices to deviate from fundamental value. Black (1986) states that, "the price of a stock reflects both the information that information traders trade on and the noise that noise traders trade on" (p. 532). Furthermore, because the fundamental value is unobservable, noise may influence asset prices. Rather, the deviation is not rapidly eliminated by information traders as taking a position involves a higher degree of risk.

[4] Black (1986) contrasts noise with information. Information is news about a company's fundamentals.

Instead, the price of a stock will tend to gradually revert back to the fundamental value over time. However, the average speed of the price reversion is noted as varying. In an extension of Black's noise trading model, Trueman (1988) explains why a rational manager would want to engage in such risky noise trading. As example, an investment fund manager may noise trade to send a positive signal apropos of his trading ability, especially when compensation is related to investors' perceptions of his trading ability.

Shleifer and Summers (1990) propose the noise trader approach as an alternative to the traditional efficient markets hypothesis. Their model is based on two main assumptions. First, some investors do not exhibit full rationality, thus their demand for risky assets is not fully justified by news that is important to asset prices. Second, arbitrage is limited and risky. This means that rational arbitrageurs cannot fully push prices toward their fundamental value. Taken together, the two assumptions imply that prices can deviate from fundamental value. Campbell and Kyle (1993) develop an equilibrium model where smart-money investors exhibit rational expectations and noise traders buy and sell randomly with their aggregate stock positions following an Ornstein-Uhlenbeck process. Campbell and Kyle find that noise trader risk becomes more important in high interest rate regimes. Shefrin and Statman (1994) develop a behavioral capital asset pricing theory where both noise traders and information traders interact. They argue that the paradigm of market efficiency fails because it does not incorporate the actions of noise traders. In their model, information traders use Bayesian learning rules, whereas noise traders employ non-Bayesian rules. They show that noise traders' cognitive errors impact prices, volatility, the premium for risk, the term structure, and option prices. Hong and Stein (1999) model a market with two boundedly rational agents; newswatchers and momentum traders. In their model, slow information diffusion leads to an initial underreaction by market participants because only a small number of newswatchers have all available information. However, momentum traders generate an overreaction to new information due to their momentum trading. Thus, their model attempts to capture the observed under- and overreaction of prices in the empirical literature.

De Long et al. (1990), DSSW hereafter, develop a theoretical model that shows how noise trader risk can influence security prices. In general, they show that irrational noise traders with erroneous stochastic beliefs can earn higher expected returns and influence asset prices. Their model explains various financial anomalies such as the excess volatility of asset prices, the mean reversion of stocks returns, the underpricing of closed-end mutual funds, and the Mehra-Prescott equity premium puzzle.

DSSW model the effect of noise traders on asset prices using an overlapping generations model with two-period-lived agents. They assume only two types of agents: rational sophisticated investors (*i*) and irrational noise traders (*n*). Furthermore, they assume that the economy contains only two assets; a safe asset (*s*) and a risky asset (*u*). Both assets pay a fixed real dividend (*r*), which is also the riskless rate. Sophisticated investors accurately perceive the distribution of returns from holding the risky asset, whereas noise traders misperceive the expected price of the risky asset by an independent and identically distributed (i.i.d.) normal random variable (ρ_t). Each agent's utility is assumed to be a constant absolute risk aversion function of wealth. Sophisticated investors maximize the following utility function:

$$E(U) = c_0 + \lambda_t^i[r + {}_tp_{t+1} - p_t(1+r)] - \gamma(\lambda_t^i)^2({}_t\sigma_{p_{t+1}}^2), \tag{2.4}$$

where the anterior subscript denotes the time at which expectation was taken, $\sigma^2_{p_{t+1}}$ is the one-period variance of p_{t+1}, the price of the asset, γ is the coefficient of absolute risk aversion, and λ^i_t is the amount of the risky asset held by the sophisticated investor to maximize expected utility. On the other hand, noise traders maximize the following utility function:

$$E(U) = c_0 + \lambda^n_t[r + {}_tp_{t+1} - p_t(1+r)] - \gamma(\lambda^n_t)^2({}_t\sigma^2_{p_{t+1}}) + \lambda^n_t(\rho_t). \tag{2.5}$$

Notice that the only difference between equation (2.4) and (2.5) is the last term in (2.5). This additional term captures the noise traders' misperception. The equilibrium price of the risky asset in an economy where noise traders influence security prices is as follows:

$$p_t = I + \frac{\mu(\rho_t - \rho^*)}{1+r} + \frac{\mu\rho^*}{r} - \frac{(2\gamma)\mu^2\sigma^2_\rho}{r(1+r)^2}, \tag{2.6}$$

where p_t is the equilibrium price, μ is the fraction of noise traders in the economy, σ^2_ρ is the variance of the misperception, and ρ^* is the average misperception of noise traders. The second term in (2.6) illustrates that changes in noise traders' misperceptions influence prices. Specifically, the greater the number of noise traders in the market relative to non-noise traders, the more prices will fluctuate. The final term in (2.6) is the heart of the DSSW model. It reveals that the variance of the misperception has a negative impact on prices, which results in higher expected returns. Furthermore, this term also indicates that as the number of noise traders increases, expected returns become larger.

One critique of noise trader models is that noise traders cannot survive in the market for long periods of time due to the cumulative losses they will endure (Friedman, 1953). To counter this argument, De Long et al. (1991) develop a model where noise traders earn higher returns than rational investors. Moreover, these noise traders will accumulate a large share of total wealth in the long run. Palomino (1996) shows that amateur investors may earn higher profits than rational traders in an imperfectly competitive market. This result is a consequence of the market power that amateurs wield in a small market. Shleifer and Vishny (1997) construct a model where arbitrageurs are unable to restore prices to fundamental values due to the riskiness of arbitrage. They argue that traditional textbook arbitrage is unrealistic and that in reality arbitrage requires capital and entails risk. Proposition 2 of their model supports the intuition behind most noise trader models. It shows that arbitrageurs have a limited ability in reducing the mispricing of securities and that large noise trader shocks induce larger mispricing. Standard models assert that arbitrageurs are more aggressive when prices are furthest from fundamental value. However, the Shleifer and Vishny model predicts that when prices are too far from fundamental value arbitrageurs have a less stabilizing effect on security prices. For example, Proposition 3 shows that when extreme mispricing occurs arbitrageurs will exit the market, and forego profitable opportunities. Wang (2001) examines the survival of nonrational investors in a dynamic setting. He shows that underconfidence cannot survive, however overconfidence can survive and even dominate the market. His model confirms the long-run viability of noise traders in financial markets.

Taken together, these models suggest that irrational investors, which misperceive the correct distribution of asset prices in financial markets, impact asset prices (Wang, 2001). Several empirical predictions for sin stocks are obtained from the DSSW model. First, unlike previous studies which attribute the overperformance of sin stocks to limited risk sharing, we examine whether changes in investor sentiment explain the observed high risk adjusted returns for sin stocks in the U.S. Second, we investigate in a GARCH framework whether higher sentiment volatility leads to higher sin stock volatility.

2.3 An Overview of Online Gambling

2.3.1 Online Gambling: Definition

Miriam Webster's dictionary defines gambling as "the playing of a game of chance for stakes." Recent technological advances have made it possible for gambling to take place online. Thus, a possible definition of online gambling could be, using the internet to play a game of chance for stakes. Shaffer (2004) defines online gambling as "…using an Internet connected computer to place a wager on the outcome of a sporting event or game, wager and play a game that has a random number generator associated at its source, or play card or casino type games in real time with other players that are linked by Internet connections" (pp. 5-6). Online Gambling may include the following forms of gambling: (1) fixed odds betting, (2) peer to peer betting, (3) spread betting, (4) gaming, and (5) lottery (Ranade et al., 2006).

The UK Gambling Act 2005 defines remote gambling as gambling in which individuals participate by the use of remote communication. This definition is broader than that of online gambling since it encompasses gambling via various remote communication devices, such as internet, telephone, television, radio, and any other electronic device that facilitates communication. This dissertation focuses on a narrower definition, which only includes online gambling.

2.3.2 Background on Online Gambling

2.3.2.1 Brief History of Online Gambling. Online gambling is a relatively new phenomenon, which promises to change the way in which individuals play games of chance.

Some authors suggest that online gambling represents the biggest cultural shift in gambling in the past decade (Griffiths et al., 2006). Because of its newness, the history of online gambling has yet to be well documented. According to Gamblingplanet.org, in 1994 the twin-island nation Antigua-Barbuda passed the Free Trade and Processing Zone Act which opened the door for online gambling. That same year the internet casino industry's first software developer Microgaming was founded. To date, Microgaming is a leading developer of software for the online gaming industry. According to Janower (1996), Internet Casinos, Inc. was the world's first online casino. It began operations on August 18, 1995. The gambling site included 18 different casino games and access to the National Indian Lottery. By 1999, technological advances and improved connectivity speed allowed Boss Media to release a gaming software platform which allowed multiplayer functionality and online chatting in virtual-gaming tables. In 2001, The Gambling Review Report was released in the UK. The report makes a series of recommendations and encourages the legalization of all types of online gambling. In 2002, an online gambler wins the first multimillion-dollar casino jackpot, demonstrating that large sums of money can be won online. By 2003, the UK based self-regulatory body, eCommerce and Online Gambling Regulation and Assurance (eCOGRA) is established. The mission of eCOGRA is to (1) address fair gaming practices and responsible operator conduct, (2) inform players of their rights, (3) resolve disputes between players and gaming sites, (4) set standards for the online gaming industry, and (5) alert players to safe online gaming sites (ecogra.org). eCOGRA's Seal of Approval is awarded to online gambling sites that meet three criteria: (1) games are fair, (2) casinos operate honestly and responsibly, and (3) money deposits are safe (ecogra.org). In 2005, the UK parliament passed the Gambling Act 2005, which legalizes all forms of online gambling.

In 2006, the United States congress passed the Unlawful Internet Gambling Enforcement Act of 2006 (UIGEA), which effectively illegalizes online gambling by prohibiting the transfer of electronic payments to online gambling site operators.

2.3.2.2 Global Trends in Online Gambling. According to Griffiths and Parke (2002), "…Internet gambling is global, accessible, and has 24-hour availability" (p. 313). In the past decade, global online gambling grew at an impressive rate. A recent study by KPMG estimates the revenue for global online gambling in 2008 at US$21 billion a year, with the potential of reaching US$ 30 billion by 2012. This represents a growth in revenue of 43 percent in just four years. Schopper (2002) estimates that there are 1,400 internet gambling sites around the globe, however, a single company may own several different sites. Possible reasons for the large increase in online gambling are (1) sophisticated gaming software, (2) integrated e-cash systems, (3) multilingual sites, (4) increased realism (e.g., gambling via webcams), and (5) improving customer care systems (Griffiths and Park, 2002). The rapid growth of online gambling underscores the need for academic scrutiny in all disciplines. This growth is sure to have an impact on society, which might manifest itself in different forms.

The emergence of online gambling has invoked distinct reactions from various countries around the globe. Some countries have taken steps to prohibit online gambling, while others have moved to legalize it. For example, China, Japan, South Korea, Russia, India, Australia, and the United States all prohibit many forms of online gambling. However, the United Kingdom, Antigua and Barbuda, Costa Rica and the Kahnawake Mohawk Territory in Quebec all allow online gambling.

2.3.2.3 Online Gambling Trends. Recently, some significant online gambling trends have been developing. These are (1) increased competition from traditional brick-and-mortar casinos, (2) industry consolidation, and (3) mobile gambling. The last trend has the potential to markedly increase online gambling.

Brick-and-mortar casinos have been, or are now considering, entering the online gaming market. For example, traditional casinos like Harrah's are now seeking to grow their revenues by competing in the online gaming market. To do so, Harrah's formed a new company, Harrah's Interactive Entertainment, to gain access to the online gambling market. It recently launched its online gaming website, Caesars Casino Online.com, so that it can compete in the UK online gaming market. However, not all brick-and-mortar gambling businesses support online gambling. In fact, many of them have long supported illegalization of online gambling due to fear of increased competition. Nevertheless, a recent article in the New York Times suggests that this opposition might be fading (Meier, 2010).

The gambling industry is undergoing consolidation and as a result many traditional gambling businesses are acquiring smaller online gaming businesses. For example, in 2005 International Game Technology (IGT), a manufacturer of electronic gaming equipment acquired WagerWorks, a provider of game content for online, mobile and interactive digital television.

Mobile gambling (i.e., gambling using cell phones) has the potential to increase revenues for online gaming companies. For example, a recent research report by Juniper Research finds that in Europe over 2 million people now wager over mobile phone devices.[5] The report also

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[5] Juniper Research (2010, January 9). *Good Odds for Mobile Gambling*. Retrieved January 12, 2011, from http://juniperresearch.com/viewpressrelease.php?pr=208

suggests that the increased usage of Smartphone devices, like the iPhone, have been driving this growth. As a result, many developers of computerized gaming software have been acquiring developers of cell phone gaming technology. For example, in 2008 IGT acquired Million-2-1, a developer of cell phone gaming technology.

2.3.2.4 Online Gambling in the UK. For the first time in Great Britain's history online gambling became legal when the Gambling Act 2005 was passed. The Act received Royal Assent on April 7th 2005, and went into effect September 2007. The Act represents a fundamental shift in the UK's gambling industry. It transforms the industry from one of restricted entry to a more free-market model (Light, 2007). The Gambling Act has 18 parts. Some key parts of the Act are (1) the establishment of a gambling commission, (2) protection of children and young persons, and (3) operating licenses. Part 2 of the Act calls for the establishment of a new regulatory body, The Gambling Commission. The commission is empowered to keep crime out of gambling, to ensure that gambling is conducted fairly and openly, and to protect children and vulnerable people. Part 4 of the Act discusses the protection of children and young people. Part 5 of the act approves remote operating licenses for online gambling operators.

The Gambling Act, in part, seeks to make the UK the global leader in online gambling.[6] This is in stark contrast to other countries which seek to make online gambling illegal (e.g., United States, Australia, India). The UK offers several advantages over other countries where online gambling is also legal (e.g., Antigua and Barbuda): (1) stable political environment, (2)

[6] Labour bids to put UK at heart of online gambling. (2006, October 8). *Sunday Times Business*, p 1.

developed capital markets, (3) reliable communications infrastructure, (4) pool of skilled workers, and (5) regulations that should inspire confidence among customers and investors.

2.3.2.5 Online Gambling in the U.S. The swift rise of online gambling has come under considerable criticism and political resistance in the U.S. Several concerns frequently cited are (1) underage gambling, (2) gambling while intoxicated, (3) available gambling hours (some internet casinos are open 24 hours a day), and (4) electronic cash (actual money seems to have more psychological value than electronic money) (Griffiths and Wood, 2000). These problems are not without merit. Research shows that adolescents are most vulnerable to developing pathological gambling behavior and that gambling amongst adolescents has increased in the recent past (Jacobs, 2000). Furthermore, research suggests that online gambling might increase the social cost of gambling as it mixes the “double threat” of high speed and convenient access with a technology that is attractive to youth (Kelley et al., 2001). Other areas of concern for online gambling are internet gambling in the workplace and unscrupulous operators (Griffiths and Park, 2002). Furthermore, many online gambling sites operate with little or no government supervision.

In response to all these concerns the United States Government passed legislation that prohibits online gambling. The prohibition of online gambling in the U.S. was made effective on October 13, 2006 when the Unlawful Internet Gambling Enforcement Act of 2006 (UIGEA) was signed into law by President George W. Bush. The UIGEA specifically prohibits the transfer of funds from financial institutions to online gambling sites.

Despite the passage of the UIGEA, many lawmakers insist on repealing the act. In 2009, Rep. Barney Frank introduced bill HR 2267, the Internet Gambling Regulation Consumer

Protection and Enforcement Act, which seeks to establish a federal regulatory and enforcement framework for internet gambling operators. The framework aims to ensure that operators maintain effective protections against underage gambling, compulsive gambling, money laundering and fraud. Supporters of the bill cite increased tax revenues for the government.

2.3.3 Empirical Findings for Online Gambling

The following section first discusses the current state of the literature for online gambling across all academic disciplines, then discusses the modicum of academic finance literature for online gambling, and finally examines the literature for traditional gambling.

The scholarly research for online gambling across all academic disciplines is scarce. Most of the extant research has focused on (1) the trustworthiness of online gambling sites, (2) prevalence rates for online gambling, and (3) the negative social and psychological effects of online gambling.[7] Shelat and Egger (2002) examine on- and off-line factors that influence the perceived trustworthiness of online gambling sites. They find that people base their trustworthiness on the information that is present in the website. For example, information regarding the legal status, fairness of gambling odds, and who owns or operates the casino helps to improve perceived trustworthiness. The literature also examines prevalence rates for online gambling (Griffiths, 2001; Ialomiteanu and Adlaf, 2001). For the UK, Griffiths (2001) finds that less than 1 percent of the people surveyed had ever gambled online and that there was no evidence of problematic gambling behavior. In Canada, Ialomiteanu and Adlaf (2001) conducted a telephone survey of 1,294 Ontario adults and found that 5.3 percent of the adults interviewed in the past twelve months had gambled online. The low prevalence rates found in these early

[7] Online gambling literature in finance is virtually non-existent.

studies is not surprising, given that online gambling was in its early stages. More recent studies suggest that prevalence rates are much higher today. For example, Griffiths et al. (2009) documents that approximately 5 percent of their sample had gambled online in the past 12 months. Furthermore, a recent study conducted in the United Kingdom by Nielsen Research Media found that online gambling participation grew by 40 percent in 2009.

Griffiths and Park (2002) provide an overview of the main social concerns due to the swift rise of online gambling and whether online gambling is doubly addictive. The authors conclude that online gambling has the potential to increase pathological gambling. In a more recent study, Griffiths (2009) provides an overview of the challenges of online gambling in the workplace. The paper reveals that employers should not neglect this important occurrence because it can hinder worker productivity and efficiency, which can in turn lead to lower firm profitability. Griffiths (2009) suggests several guidelines for managers so that they may minimize this unwanted employee behavior. First, managers and personnel need to take the issue of online gambling seriously. Second, develop a gambling at work policy. Finally, provide support to identified problem gamblers.

The literature has also examined the differences in online gamblers versus traditional gamblers. In a small qualitative study, Parke and Griffiths (2001) find that online gamblers differ from traditional gamblers in the following dimensions: (1) financial stability, (2) physiological effects, (3) competitions, (4) need for acknowledgment, and (5) social facilitation. Interestingly, they find that traditional gamblers exhibited greater physiological effects than online gamblers. Traditional gamblers reported more feelings of nausea and dizziness than online gamblers. Griffiths and Barnes (2008) also examine differences between internet gamblers and non-internet gamblers. Based on a self-selected sample of 473 student responses they find that males are more likely to be internet gamblers, internet gamblers are more likely to be problem gamblers, and males are more likely to be problem gamblers than females. Griffiths et al. (2009) examines the socio-demographic differences between internet and non-internet gamblers using data from the 2007 British Prevalence Survey. The authors find that internet gambling might be more conducive to problem gambling than non-internet gambling.

To the best of the author's knowledge there is only one published paper that examines online gaming in the context of finance. Bin et al. (2009) examine the short- and long-term market movements of six portfolios during and after U.S. online gambling legislative events. Their sample includes 17 online gambling event dates that span from January 1997 to December 2006. They examine short-term price movements using the multivariate regression model suggested by Cornett et al. (1996), while they apply factor analysis and the Fama-French (1993) three-factor model to examine long-term variation due to the legislative events. Their results suggest that small-cap casino operators favor illegalization and that large-cap casino operators are not as responsive to increased competition from online casinos. This study, however, does not examine the effect of gambling legislation on market betas and correlations. It is possible that the passage of very important gambling legislative events might affect stock market returns, betas, and correlations. For example, Zhang (2002) examines the impact of the passage of the Sarbanes-Oaxley Act (SOX) on U.S. firms' stock returns. She finds that U.S. firms experienced negative returns around important SOX events. Goodall (1994) finds that special events, such as the establishment of gaming in New Jersey, might cause gaming stocks to move independently from the market, suggesting a changing market correlation around these events.

There is evidence which suggests that gambling stocks are neglected by groups of investors (Hong and Kacperczyk, 2009). The nonparticipation of a particular group of investors suggests that online gambling stocks might have unique risk-return characteristics. This also suggests that online gambling stocks have different market sensitivities—betas, when compared to socially acceptable stocks. For example, many ethical funds (e.g., Aviva UK Ethical Fund, Sustainability Fund) screen out what some deem as unethical businesses, such as online gambling stocks.

For guidance on how online gambling stock portfolios might perform, we examine the limited amount of research available for traditional gambling stocks. However, the empirical results observed for traditional online gambling stocks may not be the same as those for online gambling. Traditional gaming studies find that gambling stocks exhibit positive risk adjusted returns (Davis and Sikes, 2002; Olsson, 2005; Salaber, 2007a; Fabozzi, Ma and Oliphant, 2008). However, Chen and Bin (2001) find a negative alpha for U.S. gaming stocks during the 1993 to 1997 period. Positive abnormal returns are usually attributed to the unwillingness of some investors to hold gambling stocks, thus, inducing a risk premium. These studies, however, do not examine reward-to-risk ratios (e.g., Sharpe, Treynor ratios) for gambling stocks.

Various gaming studies find betas close to unity (Goodall, 1994; Chen and Bin, 2001; Olsson, 2005; Salaber, 2007a). This implies that gambling stocks exhibit a large degree of comovement with the stock market. Additionally, studies find that beta is invariant to up and down market conditions (Chen and Bin, 2001; Salaber, 2007a). However, these studies use a relatively simple dummy variable approach to assess systematic risk across changing market conditions. A more robust approach would be to use time-varying betas.

The literature also finds that traditional gambling legislative events affect stock returns (Chen and Bin, 2001). For instance, Chen and Bin (2001) examine 20 federal and state legislative events that seek to regulate or deregulate the gaming industry. Their study examines casino gaming firms' stock performance spanning from July of 1993 to December 1997. They estimate abnormal returns around the 20 legislative events using the Multivariate Regression Model (MVRM) proposed by Binder (1985). They find that state deregulation has a negative impact on the returns of a portfolio formed of small casino operators, possibly due to increased out-of-state competition that would arise because of deregulation. Furthermore, they find that large casino operators benefited from state deregulation.

CHAPTER III

SIN STOCK RETURNS AND INVESTOR SENTIMENT

3.1 Introduction

Sin stocks are shares of companies whose main business activities include gambling, tobacco, and alcohol. The disdain of sin stocks by some investors and their unique risk-return characteristics make them good candidates for academic research. For example, the Vice Fund was created in 2002 to cater to sin investors and has had an average annualized return of seven percent since inception, versus five percent for the S&P 500. Additionally, according to a 2007 report by The Social Investment Forum, about one out of every nine dollars under professional management in the U.S. conforms to socially responsible investing criteria. This chapter continues the ongoing conversation for sin stocks and extends it by examining the possible relationship between sin investing and both individual and institutional investor sentiments.

Baker and Wurgler (2007) defined investor sentiment as, “a belief about future cash flows and investment risks that is not justified by the facts at hand” (p.129). There is a growing body of literature relating investor sentiment to the return generating process of stock market returns (Baker, Wurgler, and Yuan, 2010; Ho and Hung, 2009; Baker and Wurgler, 2007; Brown and Cliff, 2005; Lee, Jiang, and Indro, 2002; Lee, Shleifer, and Thaler, 1991).[8]

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[8] See Hirshleifer (2001) for an excellent survey on the relation between investor psychology and the stock market.

In general, these studies document a positive contemporaneous relationship between investor sentiment and stock market returns. Schmeling (2007) demonstrated that institutional and individual sentiment proxy for “smart money” and “noise trader risk,” respectively. Verma, Baklaci, and Soydemir (2008) examined the impact of individual and institutional sentiments on the returns of both the Dow Jones Industrial Average and the S&P 500. They found that investor error has a significant influence on the returns of these indices.

The literature for sin investing is in its early stages. Many researchers have documented large risk-adjusted returns for sin investing strategies (Hong and Kacperczyk, 2009; Fabozzi, MA, and Oliphant, 2008; Salaber, 2007a). Kim and Venkatachalam (2008) investigated if higher information risk (due to poor financial reporting quality) causes the abnormal returns found in sin stocks. They found that sin stocks actually exhibit superior financial reporting quality, when compared to a control group. Lobe and Roithmeier (2008) compared unethical and socially responsible stocks and found that unethical stocks have a superior risk-return tradeoff. A major limitation of these studies is that they do not shed light on the possible relationship between investor sentiment and sin stock returns. Previous empirical literature finds that sin stocks are less held by institutional investors and that social norms—non-financial attributes—might play a role in sin stock returns (Hong and Kacperczyk, 2009; Kim and Venkatachalam, 2008). These findings suggest that sin stocks might be susceptible to waves of both individual and institutional investor sentiment. Historically, extant literature conducts its empirical analyses through the prism of neoclassical finance. In this chapter, we argue that a behavioral approach, which accounts for the role of investor sentiment, is a suitable paradigm when examining sin stocks.

This chapter contributes to the extant literature by fusing the sin stock literature with the investor sentiment literature. First, we investigate the relation between investor sentiment and pure sin returns. Second, we determine the channel (rational or irrational) through which individual (institutional) investor sentiment impacts pure sin returns. Third, we decompose sin returns into a market-based and pure sin component and perform empirics on these variables. Fourth, this dissertation examines the volatility of sin stocks to assess whether excess returns depend on conditional volatility and if volatility clustering and leverage effects are consistent with the data. Fifth, we extend the volatility analysis by studying the impact of investor sentiment on the formation of volatility for the sin portfolio. Lastly, using sentiments-augmented asset pricing models, we investigate whether behavioral risk factors can account for the over performance found in previous empirical studies.

Impulse response functions from vector autoregressive models indicate that both individual and institutional rational-based sentiment shocks positively influence pure sin returns. However, irrational-based shocks have a positive but insignificant effect on pure sin returns. Results from GARCH estimations show that investor sentiment affects the excess returns of sin stocks. The evidence also shows volatility clustering and leverage effects for these stocks. Moreover, volatility is positively related to excess returns when individual investor sentiment is present in the model. The evidence also suggests that noise trader risk affects volatility, but only when individual sentiment is included in model. The results from the sentiments-augmented asset pricing models suggest that both irrational individual and institutional investor sentiments positively influence sin returns. In addition, after controlling for investor sentiment, the Jensen's alpha found in previous studies disappears. These results suggest that investor sentiment rather than limited risk sharing might be driving the large returns for these stocks. Overall, the results from the empirical analyses support the fundamentals-based arguments of sin returns. However, the evidence also favors the view that investor error is a significant determinant of sin stock returns and volatility.

The remainder of this chapter is organized as follows. Section 3.2 discusses the measurement and data sources used in the empirics. Then, Section 3.3 discusses the econometric methods used in the chapter. Finally, Section 3.4 presents the results of the chapter.

3.2 Measurement and Data Sources

This section provides a description of the variables used in this study. We follow previous studies and conduct the empirical analysis using monthly data. The sample spans from January 1988 to June 2009. The data are obtained through various sources. The portfolio of sin is constructed using data obtained from The Center for Research in Security Prices (CRSP). Sentiment data are collected through Datastream. The 10-year U.S. Treasury bond, 3-month T-bill, Aaa corporate bond yield, Baa corporate bond yield, and the inflation rate are all downloaded from the Federal Reserve Bank of St. Louis (FRED). The comparables portfolio, excess return on the market (*EXRm*), small minus big premium (*SMB*), high minus low premium (*HML*), momentum premium (*MOM*), dividend yield for the CRSP value-weighted index (*DY*), and one-month treasury bill rate (*RF*) are all obtained from Ken French's website.[9]

3.2.1 Sin and Comparables Portfolios

[9] I would like to thank Kenneth French for making the data available on his website. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

The portfolio of sin (*SIN*) is defined in a similar manner to Hong and Kacperczyk (2009). It includes only stocks that are in the tobacco, alcohol, and gaming industries.[10] We select sin stocks from the universe of stocks using the following procedure. We begin by using the classification scheme of Fama and French (1997) which classifies stocks into 48 industries based on their SIC codes. The Fama-French industry group 4 pertains to the beer and alcohol sector, while industry group 5 is the smoke and tobacco sector. Stocks with SIC codes 2100-2199 belong to the tobacco group, while SIC codes from 2080 to 2085 belong to the beer group. For the gaming stocks we rely on the NAICS classification. Stocks in the 7132, 71312, 713210, 71329, 713290, 72112, and 721120 all belong to the gaming industry. Next, we define our equal-weighted comparables portfolio (*COMP*) as the arithmetic average of industry groups 2 (food), 3 (soda), 7 (fun), and 43 (meals and hotels) from Fama and French (1997).[11]

3.2.2 Measures of Investor Sentiment

Sentiment data for individual investors is obtained from the American Association of Individual Investors (AAII) survey. Each week AAII conducts a survey of its members inquiring about the likely direction for the stock market for the next 6 months. Survey participants are randomly selected from approximately 100,000 AAII members. AAII compiles these survey responses weekly and labels them as bullish, bearish, or neutral. The results from this survey are published monthly as “investor sentiment” in the AAII journal.

The sentiment data for institutional investors comes from the Investors Intelligence (II) survey and is widely recognized to predict market movements (Siegel, 1992). Investors

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[10] For more information on the construction of the sin portfolio, see Hong and Kacperczyk (2009) p. 19.
[11] Hong and Kacperczyk (2009) also define the comparables portfolio in a similar fashion.

Intelligence, based in Larchmont, New York, compiles and publishes data from a survey of investment advisory newsletters. The letters from brokerage houses are excluded from the survey in order to overcome a potential bias problem towards buy recommendations. The authors of these newsletters are professional investors, thus the II is considered a proxy for institutional investor sentiment. The survey labels the newsletters as bullish, bearish, or correction (hold).

Many researchers have used both the individual and institutional sentiment measures to examine the impact of sentiment on stock returns (Solt and Statman, 1988; De Bondt, 1993; Clarke and Statman, 1998; Fisher and Statman, 2000; Lee et al., 2002; Brown and Cliff, 2004; Brown and Cliff, 2005; Verma and Soydemir, 2008). This chapter defines individual investor sentiment (*INDSENT*) and institutional investor sentiment (*INSTSENT*) as the difference between the bullish and bearish investors.

3.2.3 Other Variables

The set of control variables for the sentiment regressions comes from the conditional asset-pricing literature and have been shown to carry non-redundant information. These are the stochastically de-trended 1-month U.S. Treasury bill return (*RFx*; Campbell, 1991; Hodrick, 1992); the difference in monthly returns on 3-month and 1-month Treasury bills (*HB3*; Campbell, 1987; Ferson and Harvey, 1991); the term spread, the spread between the 10-year U.S. Treasury bond and the 3-month T-bill (*TS*; Fama and French, 1989); the default spread, the difference between the yields on Baa and Aaa corporate bonds (*DS*; Keim and Stambaugh, 1986; Fama, 1990); the dividend yield for the CRSP value-weighted index (*DY*; Fama and French, 1988; Campbell and Shiller, 1988a, 1988b); and the inflation rate (*Infl*; Fama and Schwert, 1977; Sharpe, 2002). In addition, we follow the variable selection of Brown and Cliff (2005) and expand the set of control variables by including risk factors from the asset-pricing literature. These are the excess return on the market (*EXRm*), the small minus big premium (*SMB*), high minus low premium (*HML*), and the momentum premium (*MOM*).

3.2.4 Highlights from the Data

Table 3.1 reports the descriptive statistics for the variables used in the empirics. Notice that the sin portfolio has a mean monthly return of approximately 1.5 percent (18 percent annualized). These returns are consistent in size with those reported in Hong and Kacperczyk (2009). Figure 3.1 depicts the returns for the sin portfolio over time. The largest returns for the portfolio, over the 20 year period, occur during the latest recession. Figures 3.2 and 3.3 show the bull-bear spread for individual and institutional investor sentiment, respectively.[12]

3.3 Methodology

3.3.1 Pure Sin Returns

The first section of the chapter examines the dynamic link between pure sin returns and both individual and investor sentiments in a vector autoregressive framework. However, before doing so, we compute pure sin returns and dichotomize both investor sentiments into rational and irrational components. First, we follow Mccue and Kling (1994) and compute the "extra-market covariance" of sin returns by regressing the sin portfolio on the stock market portfolio.[13] The residuals from this regression, termed "extra-market covariance," represent pure sin effects. Thus, we estimate the following equation:

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[12] Institutional investor sentiment data was only available starting from January 1997. Thus, all analyses conducted with that variable start from January 1997.

[13] King (1966) has shown that industry effects (extra-market covariance) account for about one-half the movement in stock returns, compared to 31 percent for the market.

$$R_t = \lambda_0 + \lambda_1 R_{M,t} + ps_t\,, \tag{3.1}$$

where R_t are the sin returns, λ_0 is the constant, λ_1 is the slope of the market, $R_{M,t}$ is the return on the market, and the error term, $ps_{t,}$ is the "extra-market covariance" or pure sin return. The extra-market covariance controls for the covariance between the market and sin returns. Thus, we are able to focus our analysis on the component of sin returns that is orthogonal to market returns.

3.3.2 Sentiment Regressions

Second, we dichotomize both individual and institutional investor sentiments into rational and irrational components. To do so, we follow Baker and Wurgler (2006) and regress both sentiment proxies on a set of macroeconomic variables. The sentiment regression equations are as follows:

$$INDSENT_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + irrINDSENT_t\,, \tag{3.2}$$

$$INSTSENT_t = \theta_0 + \sum_{j=1}^{J} \theta_j Fund_{jt} + irrINSTSENT_t\,, \tag{3.3}$$

where $INDSENT_t$ and $INSTSENT_t$ represent individual and institutional investor sentiment, and $Fund_{jt}$ is the set of macroeconomic variables. Additionally, θ_0, γ_0, θ_j, and γ_j are parameters to be estimated; $irrINDSENT_t$ and $irrINSTSENT_t$ are the error terms. The residuals from equations (3.2) and (3.3) represent the irrational-based sentiment, whereas the predicted values ($IN\widehat{DSEN}T_t$ and $INS\widehat{TSE}NT_t$) correspond to rational-based sentiment.

3.3.3 Vector Autogressive Models

We estimate Sims' (1980) vector autoregressive model (VAR) to assess the dynamic relationships amongst pure sin returns and both types of investor sentiment. The rationale for using the VAR model is that it will permit one to examine the possible impact that innovations (shocks) from individual and institutional investor sentiments might have on pure sin. For comparison purposes, we also use the VAR model to examine the impact of sentiments on both the S&P 500 and a comparables portfolio. A mathematical representation of an unrestricted VAR is as follows:

$$y_t = A_0 + A_1 y_{t-1} + \ldots + A_p y_{t-p} + e_t , \tag{3.4}$$

where y_t is a k vector of endogenous variables, A_1 to A_p are matrices of coefficients to be estimated and A_0 is a vector of constants. In addition, e_t is a vector of innovations. The appropriate lag length in the VAR is determined using Akaike's information criterion (AIC). The lags in the VAR model help capture the dynamic feedback amongst the variables.

The generalized impulse response function is the main tool used for interpreting the impact of sentiment shocks on pure sin. The benefit of using generalized impulse responses is that the ordering of the variables in the VAR does not influence the impulse responses. For a detailed discussion of generalized impulse response functions, see Pesaran and Shin (1998).

3.3.4 Sentiments-augmented Asset Pricing Models

The second part of the chapter examines the risk-adjusted returns of sin stocks when both individual and institutional irrational investor sentiments are included as risk factors in an asset-pricing framework. We also examine the direction and magnitude of risk loadings for both sentiments. To make sure the results are not model specific, we estimate three sentiment-augmented asset pricing models: the Sharpe-Lintner-Mossin Capital Asset Pricing Model (CAPM), the Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model.

3.3.5 Generalized Autoregressive Models

This section describes the GARCH-in-mean model used to examine the impact of sentiment on the returns and conditional volatility of the portfolio of sin.[14] The mean equation is of the following form:

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 \Delta S_t + \varepsilon_{it},$$

$$\varepsilon_{it} \sim N(0, h_{it}), \tag{3.5}$$

where R_{it} is the monthly return on the sin portfolio or the market index, R_{ft} is the risk-free rate, S_t is the proxy for sentiment (institutional or individual). Jan_t and Oct_t are dummy variables that take into account the anomalies that have been well-documented in the literature (Lakonishok and Smidt, 1988; Keim, 1983). The conditional volatility[15] is as follows:

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1}), \tag{3.6}$$

where: (1) $I_{t-1} = 0$ if $\varepsilon_{it-1} > 0$ and $I_{t-1} = 1$ if $\varepsilon_{it-1} \leq 0$, and (2) $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and $D_{t-1} = 0$ if $\Delta S_{t-1} \leq 0$.[16] The dummy variable I_{t-1} captures the asymmetric impact of innovations on the formation of conditional volatility that has been documented in previous studies (Nelson, 1991; GJR, 1993). For example, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} \leq 0$, have differential effects on the formation of conditional volatility. Good news has an impact of β_1, while bad news has an impact of $\beta_1 + \beta_2$. When β_2 is significantly greater than zero, bad news increases volatility more relative to good news and there is a leverage effect. Additionally, the magnitude and direction of shifts in investor sentiment might influence conditional volatility distinctly, thus the dummy

[14] The estimated model is similar to Lee, Jiang, and Indro (2002).
[15] $(\Delta S_{t-1})^2$ proxies for the variance of noise trader risk, ΔS_{t-1}.
[16] Bollerslev et al. (1992) suggest that the GARCH(1,1) is suitable for most econometric applications.

variables D_{t-1} and (1-D_{t-1}) capture this effect. The risk-free rate is included in both the mean and variance equations because various studies find that the nominal exchange rate is related to the conditional volatility of stock returns (Giovannini and Jorion, 1989; and Singleton, 1989).

Assuming normally distributed errors the log likelihood function for the GARCH-in-mean model is as follows:

$$\ln(L) = -\frac{T}{2}\ln(2\pi) - 0.5\sum_{t=1}^{T}\ln h_t - 0.5\sum_{t=1}^{T}\frac{\varepsilon_t^2}{h_t}, \tag{3.7}$$

where L is the likelihood, T is the number of observations, h_t is the conditional variance, and ε_t^2 is the error term. The idea behind maximum likelihood estimation is to select parameters that maximize the likelihood of drawing the observed sample (Enders, 2004). We use the Marquardt optimization algorithm to maximize the log likelihood function.

3.4 Empirical Results

3.4.1 VAR Results

Before proceeding with VAR estimations, we need to obtain the rational and irrational components of both institutional and individual investor sentiments by estimating equations (3.2) and (3.3). Tables 3.2 and 3.3 report the results of regressing both individual and institutional investor sentiments on the set of fundamentals. As expected, the set of fundamentals explains less of the variation of individual investor sentiment than that of institutional sentiment. The lower adjusted R-squared for individual investors compared to that of institutional investors suggests that individual investors are noise traders. The high significance for some of the variables illustrates both individual and institutional investor sentiments contain a rational component. That is, a portion of the variation of the sentiment variables is due to the variation in economic (financial) fundamentals. In addition, the unexplained variation, the errors, are assumed to be due to the irrational component of sentiment (Brown and Cliff, 2005).

For the VAR estimations, we also need to compute the extra-market covariance of sin portfolio returns, which are assumed to mimic a *pure* sin return series. Table 3.4 reports the results of estimating equation (3.1). 43 percent of the variation of the sin portfolio is due to the market, while 57 percent is due to an underlying sin industry factor. The high unexplained variance confirms the importance of using *pure* sin returns, instead of sin returns. Thus, in contrast to previous studies (Hong and Kacperczyk, 2009; Fabozzi, MA, and Oliphant, 2008; Salaber, 2007a), which focus on both the market and the industry component, we focus *only* on the industry component of sin portfolio returns.

Figure 3.4 shows the generalized impulse response functions for the *pure* sin series. The upper-left-hand panel of Figure 3.4 illustrates that a shock in the rational component of individual investor sentiment, at impact, has a positive and significant effect on pure sin returns. The initial increase is followed by another month of increasing positive returns. After two months, the returns begin to decrease, but still remain positive. And after 4 months, the returns are positive but insignificant. The lower-left-hand panel of the figure shows that irrational individual investor sentiment, at impact, has a positive but insignificant effect on pure sin returns. After which, returns are positive but monotonically decreasing. Following the fourth month, the returns are near zero. In the upper-right-hand panel of Figure 3.4, the Monte Carlo constructed confidence bands indicate that pure sin returns react positively to rational-based institutional investor sentiment shocks. In the first two months, sin returns are increasing until they reach their peak in the second month. Thereafter, the returns decrease but still remain positive. After the fourth month, the impact of sentiment on pure sin returns becomes insignificant. In the lower-right-hand panel of Figure 3.4, irrational-based institutional investor sentiment has a positive but insignificant effect on pure sin. In the first three months the returns are positive but decreasing.

How does the relationship between pure sin returns and investor sentiment compare to the relation between other benchmarks and investor sentiment? To answer this question, we compare these results to the S&P 500 and a comparables portfolio. Figure 3.5 shows the generalized impulse response functions for the S&P 500 series. The upper-left hand panel of Figure 3.5 shows that individual rational sentiment has a large positive and significant impact on the returns of the S&P 500. In the first two months the returns for the market are sharply increasing, but subsequently begin to decrease until they become insignificant in the fourth month. The lower-left hand panel of Figure 3.5 shows that irrational individual investor sentiment has a positive and significant impact on stock market returns for the first two months. In the upper-right hand panel of the figure, a shock in rational institutional investor sentiment leads to increasing stock market returns for the first two months, then to decreasing positive returns for another two months. After four months, the impact becomes positive but insignificant. In the lower-right-hand panel, irrational institutional sentiment has a significant and positive effect on stock market returns for the first two months. Comparing Figures 3.4 and 3.5, it is important to note that the stock market's response to shocks in both individual and institutional rational sentiments is much larger than that of similar shocks to the pure sin series.

Figure 3.6 shows the generalized impulse response functions for the comparables portfolio. The upper-left hand panel of the figure illustrates that individual rational sentiment has a large positive and significant impact on the returns of the comparables portfolio. The returns for the comparables portfolio are monotonically decreasing until they become insignificant in the third month. The lower-left hand panel of the figure shows that irrational individual investor sentiment has a positive and significant impact on the returns of the comparables portfolio. In the upper-right hand panel of Figure 3.6, a one standard deviation innovation in rational institutional investor sentiment leads to a large positive and significant impact on the returns of the comparables portfolio. After approximately three months, the shock on the returns is rendered insignificant. In the lower-right-hand panel, irrational institutional sentiment has a significant and positive effect on the comparables returns. Comparing Figures 3.4 and 3.6, the comparables portfolio's response to shocks in both individual and institutional rational sentiments is considerably larger than comparable shocks to the pure sin series.

In summary, individual and institutional rational-based sentiments shocks illicit a positive and significant response in pure sin returns. The impulse response functions also show that shocks in both irrational sentiments elicit insignificant but positive responses in pure sin returns. In addition, we find that when compared to the market and comparables portfolios, pure sin returns are less responsive to both individual and institutional sentiment shocks.

3.4.2 Asset Pricing Results

Several studies have documented high risk-adjusted returns for sin stocks in the form of positive and significant Jensen's alpha (a measure of financial performance) when estimating conventional asset pricing models (Hong and Kacperczyk, 2009; Fabozzi et al., 2008). These returns are inconsistent with the CAPM. Some attribute the over performance of sin stocks to neglect by norm-constrained investors (Hong and Kacperczyk, 2009). That is, because some investors are unwilling to hold sin stocks, a premium is generated in the form of larger returns to entice the investors that *are* willing to buy these stocks. This view is consistent with HKZ's model of pollution or Merton's (1987) model of incomplete information. In this section, we try to shed some light on this issue. We hypothesize that the introduction of investor sentiment in the asset pricing equations causes abnormal sin stock performance to vanish. By introducing investor sentiment into an asset pricing framework, we allow for a behavioral explanation of sin stock returns. The previous literature for sin stocks returns has not examined whether behavioral models, like DSSW, are consistent with sin returns.

Table 3.5 reports the results for estimating three asset pricing models for the portfolio of sin; the capital asset pricing model (CAPM), Fama-French three-factor model (FF3), and the Carhart four-factor model (FF4). Notably, the results indicate that Jensen's alpha (the intercept) is positive for two of three specifications. Additionally, beta is close to or less than one for all three models. Furthermore, the positive and significant loading on the SMB factor indicates that sin stocks perform like small stocks while the positive and significant loading on the HML factor indicates that sin stocks perform like value stocks. The momentum factor loading indicates that momentum strategies work for sin stocks. Also, notice that *R*-squared increases considerably from the CAPM to the FF3 model confirming the additional explanatory power of the added risk factors.

Table 3.6 reports the results of the sentiments-augmented CAPM. First, only irrational institutional sentiment is added to the CAPM. The results are shown in the second and third columns of Table 3.6. Results indicate that irrational institutional sentiment has a contemporaneous positive and significant effect on sin returns. The coefficient estimate for irrational institutional sentiment is 0.07 and significant at the 5 percent level. A larger part of the variance of sin returns can be explained by including irrational institutional sentiment in the CAPM. The adjusted *R*-squared for the CAPM with irrational institutional sentiment is 0.52, whereas the adjusted *R*-squared for the CAPM without sentiment (shown in Table 3.5) is 0.44. Next, only irrational individual sentiment is added to the CAPM. The results are shown in the fourth and fifth columns of Table 3.6. The results indicate a positive and significant loading of 0.03 for irrational individual sentiment. This loading is slightly lower than the coefficient estimate (0.07) for irrational institutional sentiment. Thus, compared to individual sentiment, institutional sentiment has a larger effect on sin stock returns. Finally, both institutional and individual irrational sentiments are added to the CAPM. The results are shown in the sixth and seventh columns of Table 6. The estimated parameters for institutional and individual sentiments are 0.05 and 0.03, respectively. Both estimates are positive and significant at the 10 percent level. More importantly, when both sentiments are added to the CAPM, Jensen's alpha becomes insignificant. That is, controlling for investor sentiment effectively explains abnormal returns.

Table 3.7 reports the results of the sentiments-augmented three-factor model. Across all three specifications, the coefficient estimates for both institutional and individual irrational sentiments are positive and significant. The magnitude of the sentiment coefficients is also consistent across specifications. Specifically, institutional sentiment has a larger impact on sin returns. More importantly, the magnitude of Jensen's alpha is attenuated, becoming insignificant, and abnormal performance is lost once we control for investor sentiment.

Table 3.8 reports the results of the sentiments-augmented four-factor model. Columns six and seven of the table report the results when both sentiments are included. The coefficient estimates for institutional and individual irrational sentiments are 0.59 and 0.29, respectively. The estimates are positive and significant. Furthermore, Jensen's alpha (0.36) is positive and insignificant, indicating that sin stocks do not over perform. However, when only one of these sentiments is added to the model, Jensen's alpha is significant at the 10 percent level.

In summary, in contrast to neoclassical finance theory, the asset pricing results indicate that a consistent relationship exists between both institutional and individual irrational investor sentiments and sin portfolio returns. Moreover, the relationship is positive and significant for both types of investor sentiments. When compared to individual sentiment, institutional sentiment has a larger impact on sin portfolio returns. The loadings for institutional investors are almost twice as large as those of individual investors. More importantly, Jensen's alpha disappears once the effects of both types of sentiments are taken into account. Tables 3.6, 3.7, and 3.8 all have a common theme, which is that both institutional and individual irrational sentiments are needed to fully account for the abnormal returns found in sin stocks. These results are consistent with DSSW's model of security prices, which suggests that noise trader risk is incorporated into asset prices.

3.4.3 GARCH Results

Columns two and three in Table 3.9 report the estimation results for the GARCH model without sentiment for both the sin and market portfolios. In the mean equation for the sin portfolio (column two), the positive and significant coefficient (3.524) for the January dummy variable indicates the presence of a January effect. In the variance equation, the positive and significant coefficient of 0.191 is indicative of a leverage effect for sin stocks. That is, bad news leads to larger increases in conditional volatility in the following period. Additionally, the GARCH coefficient (0.790) is positive and significant, indicative of volatility clustering.

Column three of the table shows that all of the coefficients in the mean equation are insignificant for the market portfolio. The variance equation for the market portfolio indicates the presence of a leverage effect; however, these leverage effects are larger than the ones observed for the sin portfolio. That is, bad news has a larger influence on the volatility of the market than that of the sin portfolio. In addition, the market also exhibits volatility clustering. In contrast to the sin portfolio, the coefficient for the risk-free rate (2.613) indicates that conditional market volatility is affected by contemporaneous movements in the risk less rate.

Columns four and five in Table 3.9 report the coefficient estimates for the GARCH model with individual investor sentiment for both the sin and market portfolios. The mean equation for the sin portfolio shows a positive and significant coefficient for individual investor sentiment, 0.082, which indicates that increased investor sentiment leads to higher excess returns. Using DSSW terms, the hold-more effect dominates the price-pressure effect, thus causing excess returns to increase. In the variance equation, the positive and significant coefficient of 0.013 indicates that increased sentiment volatility during periods of bullish sentiment leads to increased volatility for the sin portfolio over the next period. On the other hand, the negative and significant coefficient of -0.008 for the variance of noise trader risk indicates that increased sentiment volatility during bearish shifts in sentiment leads to decreased volatility for the sin portfolio over the next period. The large improvement in the log likelihood function values, from -807.477 to -785.672, due to the inclusion of individual investor sentiment indicates a significant improvement in goodness of fit over the base model.

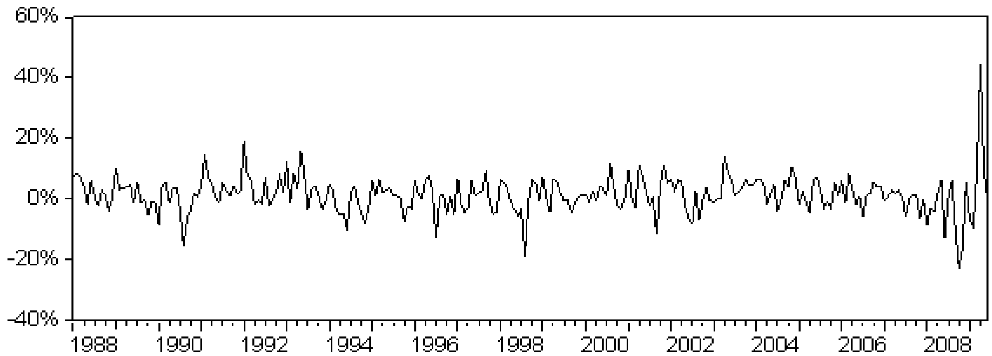
In Column five, the coefficient for the change in individual investor sentiment, 0.050, has a positive and significant impact on market excess returns. Again, indicating that the hold-more effect dominates the price-pressure effect. That is, noise traders are rewarded for the risk that they themselves create. Compared to the sin portfolio, the impact of sentiment on excess returns is slightly smaller for the market portfolio. For the market portfolio, the variance of sentiment has no significant impact on the formation of conditional volatility.

Columns six and seven in Table 3.9 report the estimation results for the GARCH model with institutional investor sentiment for both the sin and market portfolios. The coefficient for the change in investor sentiment, 0.385, indicates that in investor sentiment leads to a positive and significant increase in excess returns for the sin portfolio. In the conditional variance equation, two factors are found to be significant determinants of the conditional volatility. First, the lagged conditional volatility is found to be significant and positive, indicative of volatility clustering. Second, bullish shifts in sentiment result in decreased conditional volatility over the next period.

The results for the market portfolio indicate that excess returns are contemporaneously correlated with changes in investor sentiment. In the variance equation, there are significant leverage effects indicating that bad news has a larger impact on volatility than good news.

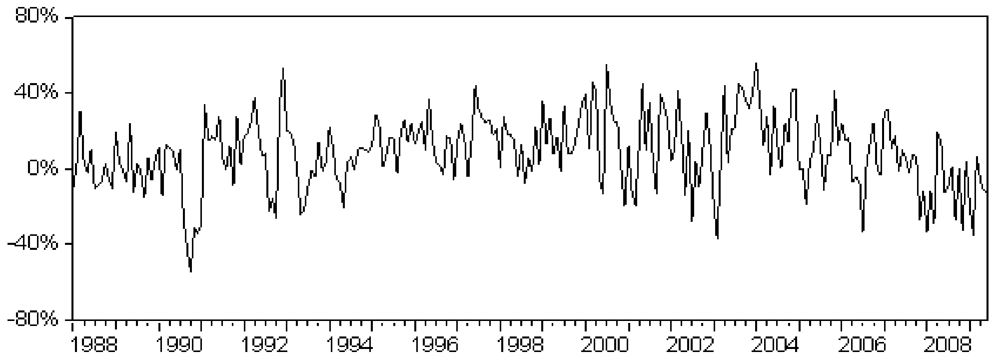
In summary, changes in both individual and institutional investor sentiment seem to have a larger impact on sin excess returns than on market excess returns. Volatility does not seem to be priced for either the sin or market portfolios. There appears to be a January effect for the sin portfolio, but not for the market portfolio. Leverage effects are larger for the market than for the sin portfolio. That is bad news has a larger impact on the volatility of the market than that of the portfolio of sin. Sin stock volatility does not seem to react to inflation or is inversely related to inflation, whereas, market volatility seems to react to inflation positively. Sin stock volatility is responsive to shifts in noise trader risk; however, the direction of the response is contingent on the sentiment proxy that is used. The introduction of either individual or institutional investor sentiment leads to a significant improvement in model fit over the baseline model, indicating that sentiment drives the return and volatility generating process.

Figure 3.1 Portfolio of Sin Returns



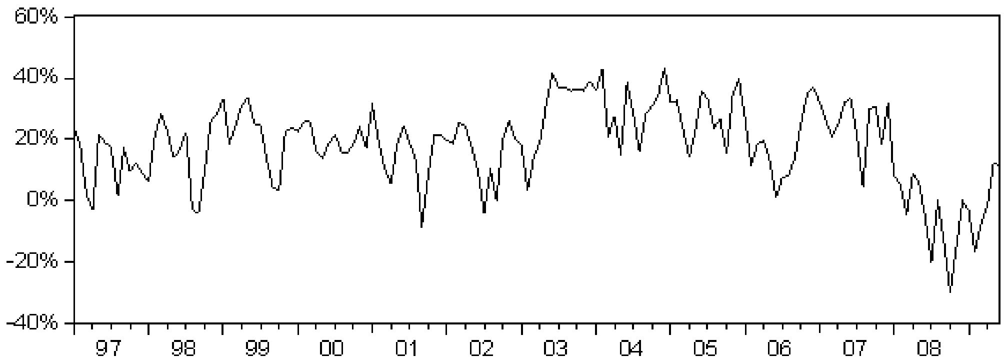
Notes: This figure shows the returns for the sin portfolio on the ordinate axis and time on the abscissa axis. The sample spans from January 1988 to June 2009.

Figure 3.2 Bull-bear Spread for Individual Investor Sentiment



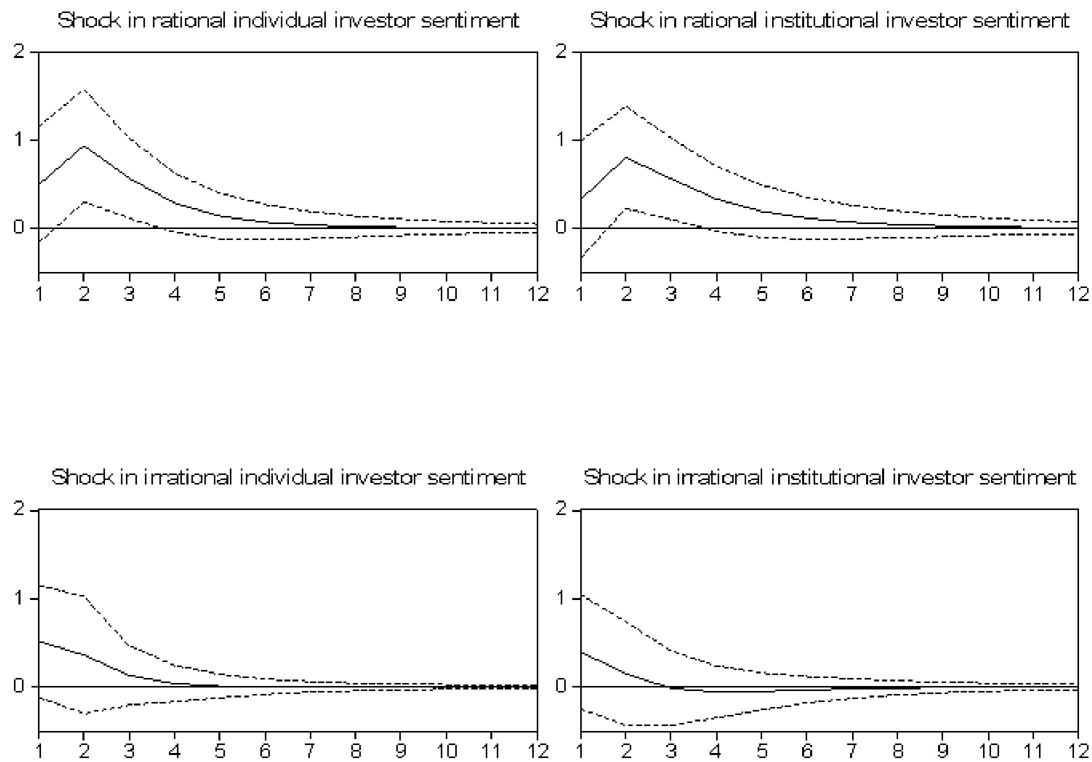
Notes: This figure shows the bull-bear spread for individual investor sentiment on the ordinate axis and time on the abscissa axis. The sample spans from January 1988 to June 2009.

Figure 3.3 Bull-bear Spread for Institutional Investor Sentiment



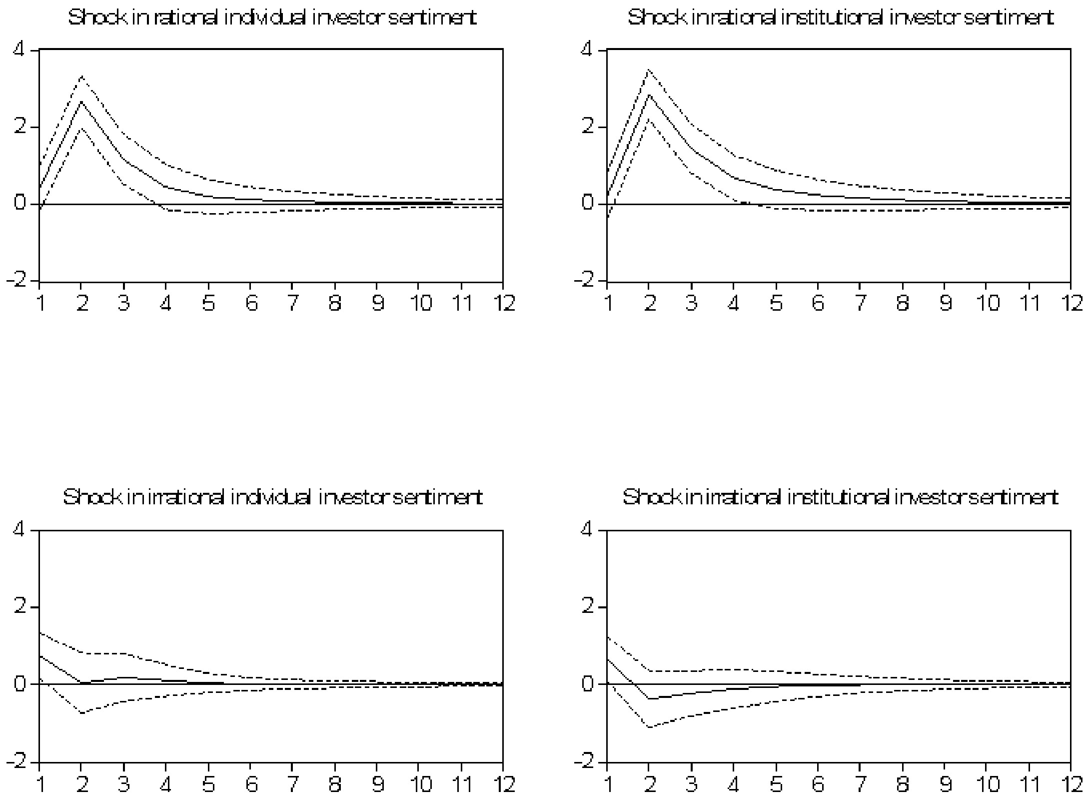
Notes: This figure shows the bull-bear spread for individual investor sentiment on the ordinate axis and time on the abscissa axis. The sample spans from January 1997 to June 2009.

Figure 3.4 Impulse Responses for the *Pure* Sin Series to a One Standard Deviation Innovation



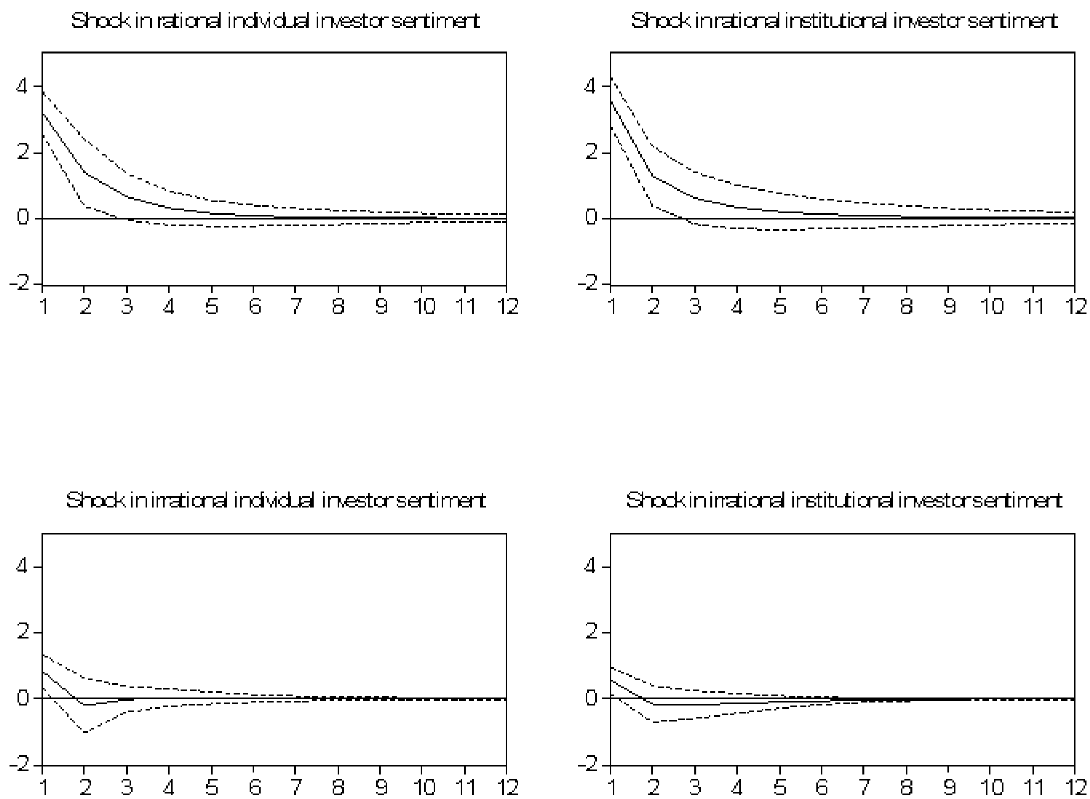
Notes: Impulse responses for the *pure* sin series to a one standard deviation innovation. Dashed lines represent upper and lower 95 percent confidence bands.

Figure 3.5 Impulse Responses for the S&P 500 Series to a One Standard Deviation Innovation



Notes: Impulse responses for the S&P 500 series to a one standard deviation innovation. Dashed lines represent upper and lower 95 percent confidence bands.

Figure 3.6 Impulse Responses for the Comparables Series to a One Standard Deviation Innovation



Notes: Impulse responses for the comparables series to a one standard deviation innovation. Dashed lines represent upper and lower 95 percent confidence bands.

Table 3.1 Descriptive Statistics

Variables	Mean	Std. dev.	Kurtosis	Skewness	Maximum	Minimum
SIN	1.461	6.177	12.584	0.828	44.520	-22.710
INDSENT	8.405	19.379	3.072	-0.204	56.100	-54.000
INSTSENT	18.091	13.670	3.479	-0.683	43.300	-29.600
RFX	-0.011	0.080	2.697	-0.221	0.204	-0.232
HB3	0.002	0.036	6.444	0.467	0.194	-0.111
TS	0.142	0.097	1.776	0.038	0.313	-0.044
DS	0.079	0.036	16.310	3.308	0.282	0.046
DY	0.872	3.773	5.463	-0.793	11.002	-17.451
INFL	0.240	0.268	15.008	-1.424	1.378	-1.672
EXRm	0.460	4.362	4.645	-0.795	11.040	-18.550
SMB	0.147	3.434	11.101	0.840	21.960	-16.790
HML	0.283	3.233	5.837	0.067	13.850	-12.400
MOM	0.684	5.158	14.037	-1.689	18.390	-34.750

Notes: All variables are in a monthly frequency. The variables are the return on the portfolio of sin (*Sin*); the bull-bear spread of individual investor sentiment (*INDSENT*); the bull-bear spread of institutional investor sentiment (*INSTSENT*); the stochastically detrended 1-month US Treasury bill return (*RFx*); the difference in monthly returns on 3-month and 1-month Treasury bills (*HB3*); the term spread, the spread between the 10-year U.S. Treasury bond and the 3-month T-bill (*TS*); the default spread, the difference between the yields on Baa and Aaa corporate bonds (*DS*); the dividend yield (*DY*); inflation (*INFL*); excess market return (*EXRm*); the small minus big premium (*SMB*); high minus low premium (*HML*); and the momentum premium (*MOM*).

Table 3.2 Individual Investor Sentiment Regression on Fundamentals

Independent variables	Coefficient estimates	Standard errors
C	27.398[a]	(4.748)
RFX	-9.136	(16.650)
HB3	9.360	(26.180)
TS	5.101	(18.407)
DS	-200.779[a]	(53.531)
DY	-1.087	(1.190)
INFL	-18.900[a]	(4.707)
EXRm	2.319[a]	(1.124)
SMB	0.806[a]	(0.483)
HML	1.728[a]	(0.602)
MOM	-0.413[a]	(0.223)
Adjusted *R*-squared	0.223	

$$INDSENT_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + irrINDSENT_t$$

Notes: All variables are in a monthly frequency. The variables are the bull-bear spread of individual investor sentiment (*INDSENT*); the stochastically detrended 1-month US Treasury bill return (*RFx*); the difference in monthly returns on 3-month and 1-month Treasury bills (*HB3*); the term spread, the spread between the 10-year U.S. Treasury bond and the 3-month T-bill (*TS*); the default spread, the difference between the yields on Baa and Aaa corporate bonds (*DS*); the dividend yield (*DY*); inflation (*INFL*); excess market return (*EXRm*); the small minus big premium (*SMB*); high minus low premium (*HML*); and the momentum premium (*MOM*). This table shows the estimated coefficients and the standard errors in parentheses: [a] denotes significance for the coefficient estimates.

Table 3.3 Institutional Investor Sentiment Regression on Fundamentals

Independent variables	Coefficient estimates	Standard errors
C	21.950[a]	(4.601)
RFX	33.545[a]	(13.653)
HB3	85.430[a]	(22.656)
TS	17.176	(16.282)
DS	-66.920	(52.973)
DY	-0.072	(0.656)
INFL	1.644	(4.237)
EXRm	1.227[a]	(0.617)
SMB	0.618[a]	(0.295)
HML	0.949[a]	(0.361)
MOM	-0.158	(0.167)
Adjusted *R*-squared	0.375	

$$INSTSENT_t = \theta_0 + \sum_{j=1}^{J} \theta_j Fund_{jt} + irrINSTSENT_t$$

Notes: All variables are in a monthly frequency. The variables are the bull-bear spread of institutional investor sentiment (*INSTSENT*); the stochastically detrended 1-month US Treasury bill return (*RFx*); the difference in monthly returns on 3-month and 1-month Treasury bills (*HB3*); the term spread, the spread between the 10-year U.S. Treasury bond and the 3-month T-bill (*TS*); the default spread, the difference between the yields on Baa and Aaa corporate bonds (*DS*); the dividend yield (*DY*); inflation (*INFL*); excess market return (*EXRM*); the small minus big premium (*SMB*); high minus low premium (*HML*); and the momentum premium (*MOM*). This table shows the estimated coefficients and the standard errors in parentheses: [a] denotes significance for the coefficient estimates.

Table 3.4 Estimation of the *Pure* Sin Series

Dependent Variable	Constant	*Market*	Adjusted *R*-squared
SIN	0.708[a]	0.932[a]	0.434
	(0.360)	(0.107)	

Notes: This table shows the estimated coefficients and the standard errors in parentheses: [a] denotes significance. *SIN* is the return on the portfolio of sin, and *MARKET* is the return on the market. We do not subtract the risk-free rate from these variables. The residuals from this regression represent *pure* sin.

Table 3.5 Asset Pricing Models Without Sentiment

	CAPM		Three-factor model		Four-factor model	
Independent variables	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors
C	0.681*	(0.358)	0.347	(0.251)	0.616**	(0.275)
EXRm	0.941***	(0.109)	1.000***	(0.074)	0.886***	(0.055)
SMB			0.724***	(0.127)	0.618***	(0.084)
HML			0.692***	(0.129)	0.703***	(0.095)
MOM					-0.275***	(0.100)
Adjusted *R*-squared	0.440		0.620		0.670	

Notes: Standard errors are in parentheses: *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. Standard errors estimated using the Newey-West estimator of the covariance matrix.

$$R_t - Rf_t = \alpha + \beta EXRm_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \phi MOM_t + \varepsilon_t$$

Where R_t-R_f is the return on the portfolio of sin net of the risk free rate. *EXRm* is the return on the market net of the risk free rate. *SMB* and *HML* are the size and book-to-market factors of Fama and French. And *MOM* is the Carhart momentum factor. ε_t is the error term.

Table 3.6 Sentiments-augmented CAPM Estimations

Independent variables	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors
C	0.696*	(0.401)	0.585*	(0.349)	0.600	(0.406)
EXRm	0.833***	(0.104)	0.858***	(0.089)	0.826***	(0.108)
irrINSTSENT	0.072**	(0.032)			0.058*	(0.033)
irrINDSENT			0.034*	(0.018)	0.031*	(0.019)
Adjusted *R*-squared	0.520		0.440		0.530	

Notes: Standard errors are in parentheses: *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. Standard errors estimated using the Newey-West estimator of the covariance matrix.

$$R_t - Rf_t = \alpha + \beta EXRm_t + \upsilon irrINSTSENT_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \omega irrINDSENT_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \upsilon irrINSTSENT_t + \omega irrINDSENT_t + \varepsilon_t$$

Where R_t-R_f is the return on the portfolio of sin net of the risk free rate. *EXRm* is the return on the market net of the risk free rate. $irrINSTSENT_t$ is irrational institutional sentiment. $irrINDSENT_t$ is irrational individual sentiment. ε_t is the error term.

Table 3.7 Sentiments-augmented Three-factor Model Estimations

Independent variables	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors
C	0.266	(0.249)	0.226	(0.240)	0.178	(0.252)
EXRm	0.965***	(0.064)	0.963***	(0.055)	0.956***	(0.066)
SMB	0.696***	(0.099)	0.683***	(0.102)	0.692***	(0.096)
HML	0.522***	(0.092)	0.653***	(0.112)	0.522***	(0.086)
irrINSTSENT	0.072***	(0.019)			0.059***	(0.018)
irrINDSENT			0.034**	(0.015)	0.029**	(0.013)
Adjusted R-squared	0.710		0.620		0.710	

Notes: Standard errors are in parentheses: *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. Standard errors estimated using the Newey-West estimator of the covariance matrix.

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \upsilon irrINSTSENT_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \omega irrINDSENT_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \upsilon irrINSTSENT_t + \omega irrINDSENT_t + \varepsilon_t$$

Where R_t-$R_{f\ is}$ the return on the portfolio of sin net of the risk free rate. *EXRm* is the return on the market net of the risk free rate. *SMB* and *HML* are the size and book-to-market factors of Fama and French. $irrINSTSENT_t$ is institutional sentiment. $irrINDSENT_t$ is individual sentiment. ε_t is the error term.

Table 3.8 Sentiments-augmented Four-factor Model Estimations

Independent variables	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors
C	0.451*	(0.244)	0.406*	(0.240)	0.363	(0.243)
EXRm	0.891***	(0.067)	0.913***	(0.054)	0.882***	(0.068)
SMB	0.645***	(0.076)	0.638***	(0.083)	0.641***	(0.077)
HML	0.556***	(0.068)	0.666***	(0.091)	0.557***	(0.063)
MOM	-0.177***	(0.055)	-0.160***	(0.059)	-0.178***	(0.054)
irrINSTSENT	0.072***	(0.018)			0.059***	(0.017)
irrINDSENT			0.034**	(0.015)	0.029**	(0.013)
Adjusted *R*-squared	0.730		0.630		0.740	

Notes: Standard errors are in parentheses: *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. Standard errors estimated using the Newey-West estimator of the covariance matrix.

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \phi MOM_t + \upsilon irrINSTSENT_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \phi MOM_t + \omega irrINDSENT_t + \varepsilon_t$$

$$R_t - Rf_t = \alpha + \beta EXRm_t + \delta SMB_t + \gamma HML_t + \phi MOM_t + \upsilon irrINSTSENT_t + \omega irrINDSENT_t + \varepsilon_t$$

Where R_t-R_f is the return on the portfolio of sin net of the risk free rate. *EXRm* is the return on the market net of the risk free rate. *SMB* and *HML* are the size and book-to-market factors of Fama and French. *UMD* is the Carhart momentum factor. $irrINSTSENT_t$ is institutional sentiment. $irrINDSENT_t$ is individual sentiment. ε_t is the error term.

Table 3.9 GARCH-in-mean Model Estimations

	Base model		Model with AAII sentiment		Model with II sentiment	
	SIN	*MKT*	*SIN*	*MKT*	*SIN*	*MKT*
α_0	0.658	0.708	-2.489***	0.725*	2.945***	0.791*
	(0.699)	(0.449)	(0.863)	(0.406)	(1.136)	(0.443)
h_{it}	0.014	-0.013	0.118***	-0.016	-0.043	-0.036
	(0.019)	(0.028)	(0.032)	(0.027)	(0.037)	(0.033)
Jan_t	3.524***	0.315	2.413**	0.158	2.348	0.390
	(0.972)	(0.718)	(0.979)	(0.817)	(2.589)	(1.062)
Oct_t	-1.885	0.058	-2.303**	-0.255	-2.079	0.996
	(1.396)	(0.963)	(1.062)	(0.829)	(2.022)	(0.928)
ΔS_t			0.082***	0.050***	0.385***	0.245***
			(0.014)	(0.011)	(0.052)	(0.026)
β_0	6.429	0.026	2.818	-0.048	22.150	2.171
	(3.653)	(0.621)	(1.857)	(0.900)	(14.283)	(2.335)
ε_{it-1}^2	-0.031	-0.001	-0.011	0.004	-0.030	0.038
	(0.034)	(0.077)	(0.029)	(0.070)	(0.070)	(0.117)
$\varepsilon_{it-1}^2 I_{t-1}$	0.191**	0.245**	0.071***	0.273***	0.479	0.834**
	(0.082)	(0.100)	(0.026)	(0.086)	(0.307)	(0.356)
h_{it-1}	0.790***	0.828***	0.856	0.815***	0.550***	0.394*
	(0.121)	(0.081)	(0.069)	(0.076)	(0.200)	(0.215)
R_{ft}	-4.807	2.613**	-1.716	2.280	-26.938	0.235
	(3.395)	(1.212)	(2.019)	(1.441)	(24.795)	(5.564)
$(\Delta S_{t-1})^2 D_{t-1}$			0.013***	0.000	-0.066***	0.022
			(0.004)	(0.002)	(0.025)	(0.021)
$(\Delta S_{t-1})^2 (1 - D_{t-1})$			-0.009***	0.001	0.024	0.004
			(0.003)	(0.003)	(0.055)	(0.011)
Log-likelihood	-807.477	-718.276	-785.672	-701.674	-453.707	-398.114

Notes: Table 3.9 reports the results from estimating the GARCH-in-mean models with and without sentiment described in the text in equations (3.5) and (3.6). The base model is estimated without sentiment. The estimation period is from January 1988 to June 2009. Note, standard errors are in parentheses: *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. *SIN* represents the return on the portfolio of sin and *MKT* is the return on the market. Moreover, R_{ft} is the risk-free rate, S_t is the proxy for investor sentiment (institutional or individual). Jan_t and Oct_t are dummy variables.

CHAPTER IV

INTERNET GAMBLING STOCK RETURNS: EMPIRICAL EVIDENCE FROM THE UK

4.1 Introduction

The internet boom spawned many new business activities, including online gambling. The online gaming industry has gone from inexistence a couple of decades ago, to millions of people wagering bets every day. According to the UK Gambling Commission, from 2008 to 2009, 68.0 percent of the population engaged in some form of gambling. Moreover, 6.0 percent of UK gamblers used the internet to engage in games of chance. A survey by ICM Research finds that participation in remote gambling (e.g., through a computer, mobile phone or interactive/digital TV) has increased over the past four years from 7.2 percent in 2006, to 9.9 percent in 2009.

The increased participation in games of chance through the World Wide Web underscores the need for academic examination of publicly listed online gaming companies. However, due to the newness of online gambling, academic finance literature in this area is virtually inexistent. Many questions remain unanswered for online gambling stocks. First, it is unclear to what degree online gambling stocks co-vary with the stock market. Second, the systematic risk (beta) for these stocks has not been quantified. Third, the financial performance of online gambling stocks relative to the market and to socially responsible investments is still unresolved.

Finally, the correlations and betas for these stocks have not been examined during the passage of an important gambling legislative event, such as the Gambling Act 2005.

This dissertation's chapter contributes to the literature in the following distinct ways. First, we examine the financial performance of an online gambling portfolio, and then compare it to both the market and socially responsible portfolios. Second, the chapter investigates whether market sensitivities are time-varying for an online gambling portfolio. Third, we examine dynamic correlations between the market and online gaming portfolio. Fourth, we document the effect of UK gambling legislation on the conditional betas and correlations of the online gambling portfolio.

The chapter yields several interesting results. First, unconditional and conditional financial performance measures indicate that the online gaming portfolio underperforms both the market and socially responsible portfolios. Second, the online gaming portfolio's beta is less than one, which indicatives defensiveness towards the market. Third, the conditional correlation between the market and online gambling portfolio is small when compared to the correlation of the market and the socially responsible portfolio. Finally, findings suggest that the Gaming Act 2005 increases the conditional correlation between the market and online gambling portfolio. Furthermore, it also increases the conditional betas for the online gambling portfolio.

The remainder of this chapter is organized as follows. Section 4.2 discusses the measurement and data sources used in the empirics. Section 4.3 discusses the econometric methods. Finally, Section 4.4 presents the results of the chapter.

4.2 Measurement and Data Sources

4.2.1 Data and Variables

The sample spans from January of 2001 to December 2009.[17] Data is collected on a monthly frequency from Datastream.[18] The main variable of interest in this empirical inquiry is the equally-weighted internet gambling portfolio (*IGAM*).[19] The portfolio includes all online gambling companies listed on the UK stock exchange since 2001. The portfolio is composed of many leading online gambling companies, such as PartyGaming, Sportingbet, and 32RED. The FTSE All-Share index (*MKT*) is used to characterize the performance of the UK market. The FTSE All-Share index is value-weighted and is composed of 630 constituents. The combined market capitalization of these constituents represents approximately 98.0 percent of the UK's market capitalization. To contrast the performance of the online gambling portfolio we also obtain monthly prices on the FTSE4Good (*FTSE4G*) index, which represents socially responsible companies in the UK. The FTSE4Good index has several inclusionary and exclusionary criteria. To be included in the index companies need to show that they are working towards environmental management, climate change mitigation and adaptation, countering bribery, upholding human and labor rights, and supply chain labor standards. More importantly, their exclusionary criterion shuns socially *irresponsible* companies such as tobacco producers and weapons manufacturers. The 3-month UK t-bill (*Rf*) is used as the surrogate for the risk-free rate of interest.

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[17] The sample begins in 2001 because this is when we first obtain data for publicly traded online gambling companies from Datastream.

[18] Monthly, instead of daily or weekly data were selected due to the problem of non-synchronous trading or non-trading problem that occurs when firms are initially listed on the UK stock exchange.

[19] Results are qualitatively the same using value-weighted portfolios.

Continuously compounded returns for all three portfolios (indexes) are calculated by applying the following formula, $R_{p,t} = \ln(P_t/P_{t-1})*100$, where P_t is the price in month t and $R_{p,t}$ represents the continuously compounded monthly return of portfolio p at time t. The sample consist of a total of 108 observations, however, one observation is lost when the monthly continuously compounded returns are calculated. In addition, the monthly risk-free rate is calculated by dividing the annualized interest rate by twelve months.

4.2.2 Highlights from the Data

Table 4.1 reports the descriptive statistics for the online gambling, market, and socially responsible portfolios and the risk free rate of interest. The mean monthly returns over the entire sample period are -0.303% for the online gambling portfolio (-3.636% annually), -0.192% for the socially responsible index (-2.304% annually), and -0.084% for the market portfolio (-1.008% annually). Compared to the market and the FTSE4good portfolios, the online gambling portfolio had the worst mean monthly return over the sample period. The low return for the online gambling portfolio is in contrast to the average returns found in Chapter 3 for the sin portfolio. As for risk, the standard deviations are 14.305% for the online gambling portfolio, 4.616% for the socially responsible portfolio, and 4.608% for the market portfolio. Over the sample period, the standard deviation for the online gambling portfolio was more than two times larger than that of the socially responsible and market portfolios. The large standard deviation for the online gambling portfolio is consistent with the standard deviations found in Chapter 3 for the sin portfolio. The mean monthly return for the risk less rate over the period was 0.340% (4.08% annually) and the standard deviation was 0.119%. The sample covers the latest financial crisis, so the poor performance for all three portfolios is to be expected.

Figure 4.1 plots the monthly returns for the online gambling portfolio. The monthly returns for the online gambling portfolio during 2005 were especially volatile, perhaps due to the passage of the Gaming Act 2005. Moreover, the figure indicates that there are clusters of volatility, implying heteroskedasticity. Figure 4.2 plots the monthly returns for the market portfolio. The figure shows that the returns exhibited a large degree of volatility during the recent financial crisis. Figure 4.3 plots the monthly returns for the socially responsible portfolio. The returns for this portfolio also exhibited large degree of volatility during the 2001 and 2008 recessions.

4.3 Methodology

This section discusses some of the methods used to estimate the financial performance, betas, and correlations for the stock market, online gambling, and socially responsible portfolios.

4.3.1 Unconditional Performance Measures

Jensen (1968) developed a financial performance measure (Jensen's alpha) and then tested it on 115 mutual funds over the period of 1945 to 1964 using annual data. He found that the mutual funds, on average, were unable to outperform a simple buy-the-market-and-hold policy. We use this measure to examine the financial performance of the online gambling and socially responsible portfolios by estimating the following equation:

$$\alpha_p = \left(R_{p,t} - R_{f,t}\right) - \beta_p\left(R_{m,t} - R_{f,t}\right) - \varepsilon_{p,t}, \tag{4.1}$$

where $R_{p,t}$ is the return on the pth portfolio at time t, $R_{f,t}$ the risk-free rate, $\varepsilon_{p,t}$ the unobservable stochastic white-noise process, β_p is the beta for the pth portfolio, and α_p is Jensen's alpha. A statistically significant positive Jensen's alpha suggests overperformance for the pth portfolio, whereas a statistically significant negative alpha indicates underperformance even after controlling for systematic risk. Furthermore, an alpha of zero is indicative of no under or overperformance of portfolios, which is consistent with the CAPM.

Sharpe (1966) developed a simple, yet theoretically meaningful ratio which measures a portfolio's excess return relative to total risk.[20] He then tested it on 34 open-end mutual funds during the period of 1954 to 1963. Consistent with neoclassical finance, he finds that funds with larger average returns typically exhibit larger variability. The Sharpe ratio is estimated as follows:

$$Sharpe\ ratio = \frac{(\bar{R}_p - \bar{R}_f)}{var(R_p)}, \tag{4.2}$$

where $\bar{R}_p$ represents the average return on the *p*th portfolio, $\bar{R}_f$ the average risk-free rate, and $var(R_p)$ the variance of the *p*th portfolio. The interpretation of the Sharpe ratio is straight forward. Portfolios with larger Sharpe ratios are considered more desirable by investors because they reward investors with more return for a given level of risk. A major benefit of the Sharpe ratio is that it can be estimated without assuming any equilibrium model (e.g., CAPM), whereas the Treynor ratio and Jensen's alpha necessitate such a model to be estimated (Ferruz and Sarto, 2004).

The Sharpe ratio has been criticized because it measures excess return relative to total risk, not market risk (beta). Portfolio theory suggests that diversification eliminates idiosyncratic risk and that only non-diversifiable risk should be rewarded. Treynor (1965) developed a measure of financial performance, the Treynor ratio, which measures excess return relative to non-diversifiable risk. According to Sharpe (1966), the Treynor ratio might be a better predictor

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[20] The Sharpe ratio is sometimes called the reward-to-variability ratio.

of future performance because it ignores transitory effects and focuses on more permanent relationships, such as systematic risk. The Treynor ratio is estimated as follows:

$$Treynor\ ratio = \frac{(\bar{R}_p - \bar{R}_f)}{\beta_p}, \tag{4.3}$$

where $\bar{R}_p$ represents the average return on the *p*th portfolio, $\bar{R}_f$ the average risk-free rate, and β_p the market beta of the portfolio. For the Treynor ratio, a larger value is indicative of better financial performance relative to systematic risk. Sharpe (1966) suggests that the Treynor ratio is an inferior measure of past performance, because it cannot capture the nonsystematic component of variability. This weakness is particularly important in non-diversified portfolios, which tend to exhibit larger idiosyncratic risk.

There is an ongoing discussion on whether Sharpe ratios are appropriate when average excess returns are negative (Scholz and Wilkens, 2006). This leads us to estimate three performance measures that account for periods where excess returns are negative; Israelson (2003, 2005) modified Sharpe ratio, Ferruz and Sarto (2004) modified Sharpe ratio, and Scholz and Wilkens (2006) normalized Sharpe ratio. Israelsen (2005) develops the modified Sharpe ratio and tests it as a ranking criterion using 25 U.S. equity mutual funds over the period of 1999-2003. The interesting feature of his sample is that over the sampled period all 25 funds had negative excess returns. When compared to the regular Sharpe ratio, he finds that the modified Sharpe ratio is much better at ranking funds in periods of negative excess returns. The Sharpe ratio developed by Israelsen (2003, 2005) is as follows:

$$mSR_p^{IS} = \frac{\bar{R}_p - \bar{R}_f}{var(R_p)^{\left(\frac{\bar{R}_p - \bar{R}_f}{abs\left(\bar{R}_p - \bar{R}_f\right)}\right)}}, \tag{4.4}$$

where mSR_p^{IS} is the modified Sharpe ratio for the *p*th portfolio, $\bar{R}_p$ and $var(R_p)$ are the average return and variance on the *p*th portfolio, respectably. $\bar{R}_f$ the average risk-free rate and $abs()$ is the absolute value operator. Modified Sharpe ratios that are less negative are indicative of better financial performance. For example, a modified Sharpe ratio of -0.49 is more desirable than that of -8.94. According to Israelson (2005), the value of the modified Sharpe ratio is as a ranking criterion.

Ferruz and Sarto (2004) modify the Sharpe ratio by treating the premium on returns as relative rather than absolute. Their contribution involves dividing the returns by the risk-free rate in the numerator of the Sharpe ratio. Ferruz and Sarto (2004) examine the quarterly returns of 40 equity mutual funds in Spain using the Sharpe ratio and the Ferruz and Sarto (2004) modified Sharpe ratio. They find that the rankings of the mutual funds based on these two different measures were distinct. The Ferruz and Sarto (2004) modified Sharpe ratio is estimated as follows:

$$mSR_p^{FS} = \frac{\frac{\bar{R}_p}{\bar{R}_f}}{var(R_p)}, \tag{4.5}$$

where mSR_p^{FS} is the modified Sharpe ratio for the *p*th portfolio. A larger ratio represents a more favorable reward-to-risk relationship. A weakness in this ratio is that it does not provide consistent rankings when mean returns are negative, $\bar{R}_p < 0$ (Ferruz and Vicente, 2005).

Scholz and Wilkens (2006) developed a normalized Sharpe ratio that separates the impact of the market climate and fund management performance on fund excess returns. The normalized Sharpe ratio of Scholz and Wilkens (2006) is:

$$nSR_p = \frac{JA_p + \beta_p(\bar{R}_{lm} - \bar{R}_{lf})}{\sqrt{\beta_p^2 var(R_{lm})^2 + var(R_p)^2}}, \tag{4.6}$$

where the numerator is the excess return and is obtained from the following regression:

$$R_{p,t} - R_{f,t} = JA_p + \beta_p(R_{m,t} - R_{f,t}) + \varepsilon_{p,t}, \tag{4.7}$$

where $R_{p,t}$ is the return on the *p*th portfolio, $R_{lf,t}$ is the return for the long risk-free rate, JA_p is Jensen's alpha, $R_{lm,t}$ is the long return for the market, β_p is beta, and $\varepsilon_{p,t}$ is the Gaussian disturbance term. The numerator (excess return of the fund) of the normalized Sharpe ratio is influence by fund specific variables (JA_p, β_p) and market variables ($\bar{R}_{lm}, \bar{R}_{lf}$). The denominator (variance of the fund) is also composed of fund specific variables ($\beta_p^2, var(R_p)^2$) and market variables ($var(R_{lm})^2$). Scholz and Wilkens (2006) estimate the variance and mean of both the market and risk-free rate using a "long" window. This calculation avoids the market climate bias. Thus, the normalized Sharpe ratio represents a measure of risk-adjusted performance for an "average" market period based on fund-specific characteristics. Therefore, it is not affected by random market climates and yields a more accurate appraisal of fund management performance. Scholz (2006) examines the ranking performance of the normalized Sharpe ratio on 25 U.S. open-end mutual funds. He examines the performance of these funds for a bear market, starting in January 1999 to December 2003. All funds had average mean negative excess returns during the evaluation period. Their results show that the normalized Sharpe ratio leads to better ranking of funds. A potential weakness of this approach is that it is based on a single factor model and assumes stability of the estimated parameters (i.e., intercept, slope, and error variance).

To examine statistical differences in financial performance, we use the Jobson and Korkie (1981) test of equal Sharpe ratios. The Jobson and Korkie test is as follows:

$$z = \frac{\sigma_a(\mu_b - Rf) - \sigma_b(\mu_a - Rf)}{\sqrt{\theta}}, \tag{4.8}$$

$$\theta = \frac{1}{T}\left[2\sigma_a^2\sigma_b^2 - 2\sigma_a\sigma_b\sigma_{ab} + \frac{1}{2}\mu_a\sigma_b^2 + \frac{1}{2}\mu_b\sigma_a^2 - \frac{\mu_a\mu_b}{2\sigma_a\sigma_b}\left(\sigma_{ab}^2 + \sigma_a^2\sigma_b^2\right)\right], \tag{4.9}$$

where μ_j is the mean return of the *j*th portfolio, σ_j is the standard deviation of portfolio *j*, σ_{ij} is the covariance between portfolios *i* and *j*, and *T* is the number of observations. Under the null hypothesis, Sharpe ratios are statistically equal. A rejection of the null indicates a distinct reward-to-risk relationship between portfolio *i* and *j*. The hypotheses are:

H_0: Portfolio i – Portfolio $j = 0$ and (4.10)

H_1: Portfolio i – Portfolio $j \neq 0$, $i \neq j$. (4.11)

Using Monte Carlo methods, Jobson and Korkie (1981) find that the *z* statistic is well behaved in small samples. However, they also find that the test lacks power in detecting typical differences in Sharpe ratios when monthly data is used.

4.3.2 Conditional Performance Measures

In the previous section, the financial performance measures where unconditional and did not allow for time-varying parameters (e.g., variances, intercepts, and betas). Evidence suggests that the assumption of homoscedasticity in financial returns is not always realistic and that parameters might be time-varying. Various authors propose econometric models that account for the unequal variances sometimes found in financial returns (Engle, 1982; Bollerslev, 1986; Glosten, Jagannathan, and Runkle, 1993). In this section we modify the unconditional financial performance measures (Sharpe and Treynor ratios) and allow for time-varying parameters.

First, the unconditional Sharpe ratio from equation (4.2) is modified by assuming that the variance of the portfolio, denominator, is time-varying. To estimate this ratio we now need the estimated time-varying variance. Various researchers have developed econometric models that generate these time-varying variances. Engle (1982) introduced a new class of stochastic processes. He developed the autoregressive conditional heteroscedasticity (ARCH) model, which explicitly assumes that the conditional variance is a function of past squared shocks. Bollerslev (1986) extends Engle's pioneering work by introducing lagged conditional variances when modeling the conditional variance function. Glosten, Jagannathan, and Runkle (1993) account for leverage effects–where volatility responds asymmetrically to price changes–using a threshold GARCH model, also known as a GJR model. An advantage of the GJR model over the ARCH and GARCH models is that a dummy variable separates the impact of past negative (positive) shocks on volatility. The GJR model is as follows:

$$R_{p,t} = \mu + \varepsilon_t,\ \sim N(0, h_t), \tag{4.12}$$

$$h_t = \gamma + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \omega\varepsilon_{t-1}^2 S_{t-1}^-, \tag{4.13}$$

where in the mean equation $R_{p,t}$ represents the return on portfolio p at time t, μ the constant, ε_t the unobservable error. In the variance equation, h_t represents the conditional variance, ε^2_{t-1} the lagged error term, $S_{t-1}^- = 1$ for $\varepsilon_{t-1} < 0$ and 0 otherwise, and subject to $\gamma > 0$, $\alpha, \beta \geq 0$, $\alpha + \omega \geq 0$, $\alpha + \beta + \omega < 1$. Volatility asymmetry is captured through ω. Accordingly, we take the volatility generate by the GJR GARCH and use it as an input in the denominator of the Sharpe ratio, where the Sharpe ratio now becomes:

$$Sharpe\ ratio_t = \frac{(\bar{R}_{p,t} - \bar{R}_{f,t})}{var(R_{p,t})}, \tag{4.14}$$

where time subscripts have been added to the variables to denote the time-varying nature of the ratio.

Second, the unconditional Treynor ratio from equation (4.3) is modified by assuming that the beta of the portfolio, denominator, is time-varying. Thus, the Treynor ratio becomes:

$$Treynor\ ratio = \frac{(\bar{R}_{p,t} - \bar{R}_{f,t})}{\beta_{p,t}}, \tag{4.15}$$

where time subscripts are added to denote that beta is time-varying. To estimate this ratio we now need the estimated time-varying beta. The conditional beta is estimated using the conditional variances and co-variances obtained from Engle’s (2002) dynamic conditional correlation (DCC) model.

4.3.3 Betas and Correlations

Since the development of the CAPM over forty years ago, betas have become critical inputs in financial decision making. The beta of a portfolio is important in mutual fund applications, portfolio optimization, and cost of capital estimation (Franzoni, 2006). Furthermore, betas are also used as weights in hedging strategies. Studies have traditionally assumed that beta is a constant parameter that does not change thorough time (Black, Jensen, and Scholes,1972; Blume and Friend, 1973; Fama and MacBeth, 1973). However, anomalies discovered in the late 1970s have cast doubt on the assumption of parameter stability. Therefore, more recent studies allow for beta to vary over time (Jagannathan and Wang, 1996; Ferson and Harvey, 1999; and Lettau and Ludvigson, 2001). A widely used method for estimating time-varying betas is to use a rolling regression procedure. A more refined approach is to model the time-varying betas by using multivariate GARCH models such as Engle’s (2002) dynamic conditional correlation model. Tsay (2005) suggests that conditional (time-varying) beta may be estimated using multivariate volatility models. Various researchers have used multivariate GARCH models to estimate time-varying betas (Ledoit, Santa-Clara, and Wolf, 2003; Jostova and Philipov, 2005; Chong, Her, and Phillips, 2006).

Many authors document temporal variation in market risk loadings (betas) through the use of a rolling regression procedure (Fama and French,1997; Groenewald and Fraser, 2000; Franzoni, 2006; Fama and French, 2006; Perez Liston and Soydemir, 2010). The strength of this approach is its ease of application. However, a weakness of this approach is that it relies on selecting an optimal window length. Unfortunately, there is no guidance on what the appropriate window length should be. Given the frequency of our data and the length of our sample, we estimate the time-varying parameter beta using a rolling window of 12 months with one-month increments. Many authors use different window lengths. A common rule is to use a relatively long window, 5-years (Franzoni, 2006). On the other hand, Fama and French (2006) evaluate different window lengths for estimating betas and find that a 1-year window length is more suitable. Furthermore, if beta exhibits substantial volatility and a long window is chosen, then beta will seem less volatile than what it really is. Perhaps due to these difficulties, there is evidence which suggests that rolling regression estimation does not completely capture true systematic risk (Ledoit, Santa-Clara, and Wolf, 2003; Jostova and Philipov, 2005). For example, Jostova and Philipov (2005) find that although rolling regressions provide reasonable estimates of the average beta, the procedure fails to adequately capture time-variations in systematic risk. Furthermore, Jostova and Philipov (2005) compare the estimated betas obtained from the rolling regression and the GARCH model to those of the true-betas and find that the root mean square error (RMSE) is lower for the GARCH model (0.12) and higher for the rolling regression (0.21). Thus, the GARCH model provides more accurate estimates of time-varying systematic risk.

The estimation of conditional betas requires, as inputs, conditional variances and co-variances, which are obtained through Engle's (2002) dynamic conditional correlation model. The conditional beta is as follows:

$$\beta_{p,t} = \frac{cov(R_{p,t}, R_{m,t})}{var(R_{m,t})}, \tag{4.16}$$

where $var(R_{m,t})$ is the conditional variance of the market portfolio and $cov(R_{p,t}, R_{m,t})$ is the conditional covariance between the relevant portfolio and the market.

Correlations are critical inputs for the tasks of the financial community. Correlations are useful in options and hedging strategies and asset allocation and risk assessment. Academics, practitioners, and Wall Street researchers have long sought reliable estimates of correlations between assets (Engle, 2002). A widely used method of estimating correlations is through historical rolling correlations. A more sophisticated approach is to model the conditional correlation using multivariate GARCH models such as the dynamic conditional correlation model.

A widely used method for estimating time-varying correlations is through historical rolling correlations. The rolling correlation estimator for returns with zero mean is as follows:

$$\hat{\rho}_{12,t} = \frac{\sum_{s=t-n}^{t} R_{1,s} R_{2,s}}{\sqrt{\left(\sum_{s=t-n}^{t} R_{1,s}^2\right)\left(\sum_{s=t-n}^{t} R_{2,s}^2\right)}}, \tag{4.17}$$

where $\hat{\rho}_{12,t}$ is the estimated correlation at time *t*. A major drawback of this estimator is that it gives equal weight to all observations less than *n* periods in the past and ignores observations older than *n* periods (Engle, 2002). In addition, the length of the moving window might influence the results.

Time-varying correlations are also estimated using Engle's (2002) dynamic conditional correlation model. The model is of the following form:

$$Q_t = (1 - a - b)\bar{Q} + a(\Xi_{t-1}\Xi'_{t-1}) + bQ_{t-1}, \tag{4.18}$$

where a and b are non-negative scalar parameters that satisfy, $0 < a + b < 1$. The unconditional covariance matrix is $\bar{Q}$, Ξ_{t-1} is the lagged standardized innovation vector, Q_{t-1} lagged variance matrix. The time-varying correlation matrix R_t is:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{4.19}$$

where Q_t^* is a diagonal matrix with the square root of the diagonal elements of the variance-covariance matrix Q_t. The normalization matrix, Q_t^* guarantees that R_t is a correlation matrix.

4.4 Empirical Results

4.4.1 Unconditional and Conditional Performance Measures

Table 4.2 reports the results for the unconditional Sharpe ratios. The unconditional Sharpe ratios are -0.04, -0.12, and -0.09 for IGAM, FTSE4G, and MKT, respectively. Notice that IGAM has the better reward-to-variability ratio and FTSE4G has the worst Sharpe ratio. Table 4.3 reports the results of calculating the Jobson and Korkie test of equal Sharpe ratios. The test's null hypothesis is that the Sharpe ratios are equal, or that both portfolios have similar reward-to-variability ratios. A rejection of the null would indicate that one portfolio has a superior reward-to-variability ratio. For all three pair-wise comparisons, we fail to reject the null of equal Sharpe ratios, indicating that all three portfolios have similar reward-to-variability ratios. However, the failure to reject the null might be due to the low power of the test. Jobson and Korkie (1981) and

Jorion (1985) indicate that because of the lower power of the test, large differences in Sharpe ratios need to be observed before rejecting the null.

Table 4.2 reports the results for the conditional Sharpe ratios. The conditional Sharpe ratios are -0.05, -0.13, and -0.10 for IGAM, FTSE4G, and MKT, respectively. The conditional versions of the ratios reveal a slight worsening in the reward-to-variability relationship for all three portfolios. However, the rankings between the three portfolios remain intact.

Table 4.4 reports the results for the modified and normalized Sharpe ratios. The Israelson (2003, 2005) modified Sharpe ratios are -0.053 for FTSE4G, -9.211 for IGAM, and -1.950 for MKT. The Ferruz and Sarto (2004) modified Sharpe ratios are -0.122 for FTSE4G, -0.062 for IGAM, and -0.053 for MKT. Scholz and Wilkens (2006) normalized Sharpe ratios are 0.003 for FTSE4G and -0.019 for IGAM. After estimating reward-to-variability measures that account for periods when average excess returns are negative, the results reveal a different story. Out of the three measures only in one does IGAM outperform both the FTSE4G and market portfolios. These results are in contrast to the unconditional and conditional Sharpe ratios measures presented earlier. Thus, over the 2001 to 2009 period IGAM underperformed relative to the FTSE4G and the market portfolios.

Table 4.2 reports the unconditional Treynor ratio for IGAM and FTSE4G. The Treynor ratios are -1.04 and -0.58 for IGAM and FTSE4G, respectively. Accounting only for systematic risk, FTSE4G outperforms the online gaming portfolio. The table also reports the conditional Treynor ratio for IGAM and FTSE4G. The estimated conditional Treynor ratios are -0.78 and -0.60 for IGAM and FTSE4G, respectively. Again, FTSE4G outperforms IGAM, however, by a smaller margin, when compared to unconditional measures.

The results for estimating the CAPM for IGAM and FTSE4G are presented in Table 4.2. For IGAM, the CAPM yields a Jensen's alpha of -0.381, which is statistically indistinguishable from zero. In contrast to previous sin studies, there is no overperformance for the online gambling portfolio (Hong and Kacperczyk, 2009; Fabozzi, Ma, and Oliphant, 2008; Lobe and Roithmeier, 2008). This implies that online gambling investors do not receive a risk premium for investing in socially irresponsible firms. For FTSE4G, alpha is -0.142 (or 14 basis points per month) and statistically significant at the 10% level. Consistent with previous studies, the negative estimated alpha implies that socially responsible investors bear a cost for investing in responsible companies (Geczy, Stambaugh, and Levin, 2003; Renneboog, Horst, Zhang, 2008).

The results from the three different financial performance measures—Sharpe ratios, Treynor ratios, and Jensen's alpha—suggest that the online gambling portfolio underperformed both the FTSE4G and market portfolios over the 2001 to 2009 period. These results are in contrast to those from Chapter 3. There I find that the portfolio of sin over performs relative to the market. Specifically, the results from the various Sharpe ratios—unconditional, conditional, modified, and normalized—suggest that, once we account for negative excess returns, the online gambling portfolio has the lowest ranking relative to the other two portfolios. The unconditional and conditional Treynor ratios also rank the online gambling portfolio below the FTSE4G. Although, not statistically significant, Jensen's alpha for the online gambling portfolio is considerably lower than that of FTSE4G portfolio.

4.4.2 Unconditional, Conditional, and Rolling Betas

This section presents the results from estimating beta using: (1) the static CAPM, (2) a rolling regression procedure, and (3) a multivariate GARCH model.

Static CAPM estimation results for the online gambling portfolio and the socially responsible portfolio are presented in Table 4.2. The beta for the online gambling portfolio is 0.618 and statistically significant at the 1% level, whereas beta for the socially responsible portfolio is 0.919 and statistically significant at the 1% level. A beta of less than one for the online gambling portfolio is consistent with previous sin stock studies (Olsson, 2005; Salaber, 2007a; Salaber, 2007b; Lobe and Roithmeier, 2008). Consistent with studies on socially responsible investing (Kempf and Osthoff, 2007), beta for the socially responsible portfolio is close to unity indicating a close co-movement with the market.

Table 4.5 reports the descriptive statistics for the estimated betas using the rolling regression procedure for both the online gambling and socially responsible portfolios. The online gambling portfolio has an average beta of 1.08, indicating greater systematic risk relative to the market portfolio. The online gambling portfolio has a maximum beta of 3.51 and a minimum of -0.05. The large standard deviation of the estimated betas for the gambling portfolio suggests a large degree of variability over the period. On the other hand, the socially responsible portfolio has an average estimated beta over the sample period of 0.90, indicating that it is slightly defensive. Its maximum beta was 1.05, while its minimum was 0.74. The standard deviation (0.06) of the betas for the socially responsible portfolio is much smaller than that of online gambling portfolio.

Figure 4.4 depicts the rolling betas for both the online gambling portfolio and the socially responsible portfolio. The main result from this figure is that UK gambling legislative events had a considerable impact on the systematic risk of the online gambling portfolio. Notice that from the beginning of 2005 to mid-2006, beta increased from less than 1 to above 3. In contrast to the static CAPM, which provides no information about the variability of beta over time, the rolling regression procedure reveals a different story. The procedure shows, mainly, that the beta for the online gambling portfolio has fluctuated considerably over the sample period.

Table 4.5 also reports the descriptive statistics for the conditional betas estimated by using the variances and co-variances obtained from the DCC model for both the online gambling and socially responsible portfolios. The online gambling portfolio has an average beta of 0.84. A means test on the conditional betas for the online gambling portfolio indicates that its mean is statistically different from zero. Moreover, the mean conditional beta for online gambling portfolio is statistically less than one, indicating defensiveness towards the market portfolio. Previous research finds that sin stocks are defensive (Olsson, 2005; Salaber, 2007a; Salaber, 2007b; Lobe and Roithmeier, 2008). The online gambling portfolio has a maximum beta of 2.81 and a minimum of 0.29. The standard deviation for the online gambling portfolio is 0.43, indicating large variability over the period. In contrast, the socially responsible portfolio has an average estimated beta over the sample period of 0.89, indicating that it is slightly defensive. Furthermore, a means test on the conditional betas of the socially responsible portfolio indicates that its mean is statistically different from zero. Its maximum beta was 1.17, while its minimum was 0.69. The standard deviation (0.11) of the betas for the socially responsible portfolio is much smaller than that of online gambling portfolio.

We perform a *t*-test of equal means for the conditional betas of the online gambling and socially responsible portfolios. The results indicate that they are indistinguishable from each other. However, due to the non-normality of the data, we perform a test of equal median. The results indicate that the median for the conditional betas are distinct at the 1 percent level. In addition, we test for the equality of the variances of the conditional betas. The results indicate that the variances are not equal, meaning that the uncertainty of the sensitivity of the online gambling portfolio to the market is greater than that of the socially responsible portfolio to the market.

Table 4.6 reports the correlation between the conditional betas of the online gambling portfolio and the socially responsible portfolio. The correlation coefficient is -0.17 and statistically significant at the 10 percent level. The opposite nature of these portfolios, social responsibility versus social irresponsibility, might cause a distinct reaction to stock market variation. Perez Liston and Soydemir (2010) find that time-varying betas of sin and faith-based portfolios correlate negatively over time.

Figure 4.5 plots the conditional betas for both the online gambling and socially responsible portfolios over time. The conditional betas for the online gambling portfolio range from a minimum of 0.294 to a maximum of 2.812, whereas for the socially responsible portfolio they range from a minimum of 0.692 to a maximum of 1.168. At the start of 2005, online gambling betas increase very quickly. They reach a maximum of 2.81 in the last quarter of 2005, and then fall to a pre-2005 level. The results suggest that the passage of the Gambling Act 2005 had a short- to midterm impact on the market sensitivities for the online gambling portfolio. From an online gambling investor's point of view, higher conditional betas for online gambling stocks result in increased overall portfolio risk. Given that an investor's portfolio risk, in a diversified portfolio, is just the weighted average of the individual securities betas. That is, legislative events tend to increase the systematic risk of an investor's portfolio.

4.4.3 Conditional and Rolling Correlations

This section presents the results of estimating time-varying correlations with the market for both the online gambling and socially responsible portfolios. The correlations are estimated using a rolling procedure, and then using Engle's (2002) dynamic conditional correlation model.

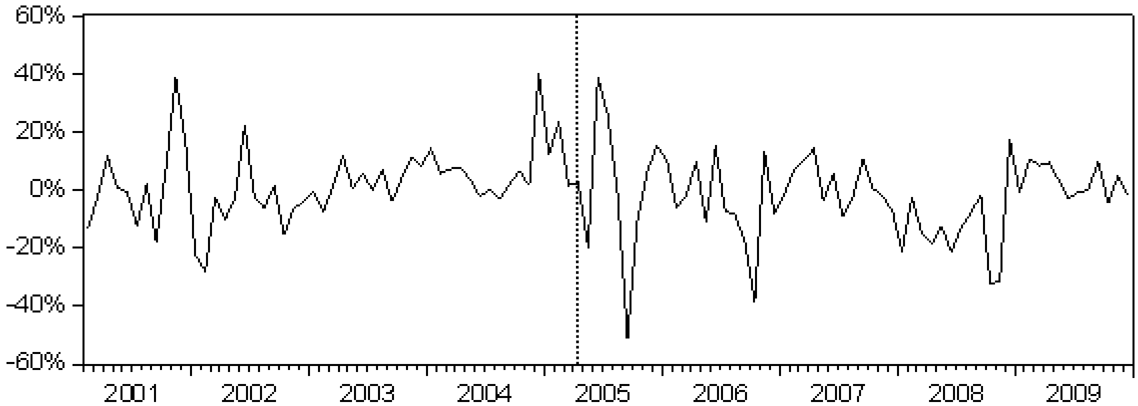
Table 4.7 reports the descriptive statistics for the time-varying correlations with the market for both the online gambling and socially responsible portfolios estimated by using a rolling regression procedure. The online gambling portfolio has an average correlation coefficient with the market of 0.21, indicating a weak co-movement with the market over the sample period. The online gambling portfolio has a maximum correlation of 0.61 and a minimum of -0.51. The correlation coefficient exhibits a large degree of variability as can be seen by the large standard deviation (0.20) of the estimated correlations. On the other hand, the socially responsible portfolio has an average estimated correlation with the market of 0.90. Its maximum correlation was 0.98, while its minimum was 0.74. The standard deviation (0.05) of the correlations for the socially responsible portfolio is much smaller than that of online gambling portfolio.

Figure 4.6 depicts the rolling correlations with the market for both the online gambling portfolio and the socially responsible portfolio. Notice that from the second quarter of 2004 to mid-2006, the correlations with the market for the online gambling portfolio increased. Post-2005, the correlations then decreased and even turned negative towards the end of the sample. However, the impact of the Gambling Act 2005 is not very clear.

Table 4.7 also reports the descriptive statistics for the conditional correlations with the market for both the online gambling and socially responsible portfolio. The correlations are obtained by using the DCC model. The online gambling portfolio has an average correlation with the market of 0.24. The online gambling portfolio has a maximum correlation of 0.86 and a minimum of -0.05. The standard deviation for the correlation is 0.12, indicating large variability for the correlation coefficient over the period. In contrast, the socially responsible portfolio has an average estimated market correlation over the sample period of 0.91, indicating a large degree of co-movement with the market. Its maximum correlation coefficient was 0.94, while its minimum was 0.85. The standard deviation (0.02) of the correlation for the socially responsible portfolio is rather small relative to that of online gambling portfolio.

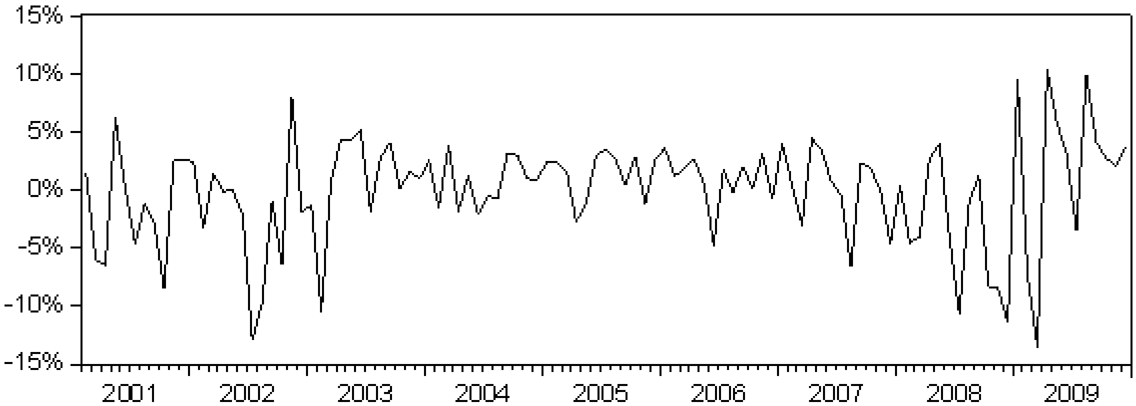
Figure 4.7 plots the conditional correlations with the market for both the online gambling and socially responsible portfolios over time. Similar to the conditional beta results, at the start of 2005 online gambling correlations with the market increase very quickly, then fall back to pre-2005 levels. These results also suggest that the passage of the Gambling Act 2005 had a transitory effect on the correlation of the online gambling portfolio with the market.

Figure 4.1 Online Gambling Portfolio Returns



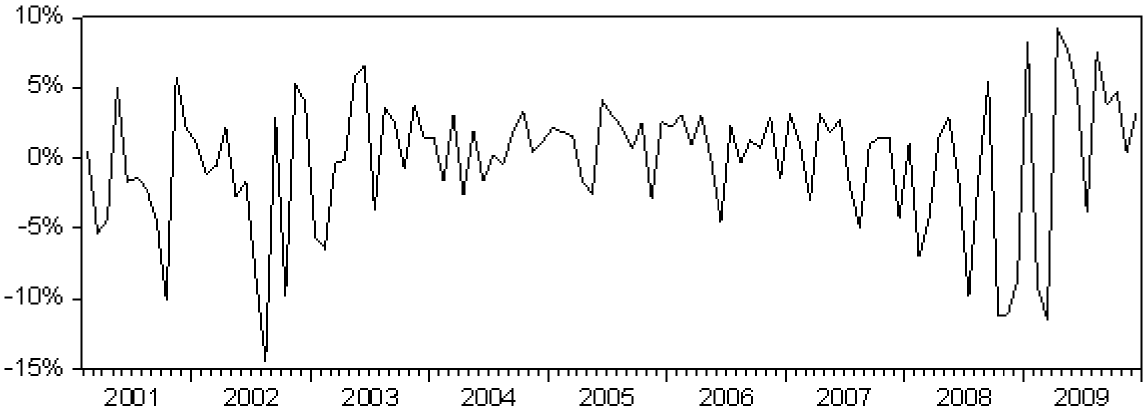
Notes: This figure shows the returns for the online gambling portfolio on the ordinate axis and time on the abscissa axis. The sample spans from January 2001 to December 2009. The dashed vertical line represents the passage of the Gambling Act 2005.

Figure 4.2 FTSE All-Share Index Returns



Notes: This figure shows the returns for the FTSE All-Share index on the ordinate axis and time on the abscissa axis. The sample spans from January 2001 to December 2009.

Figure 4.3 FTSE4Good Index Returns

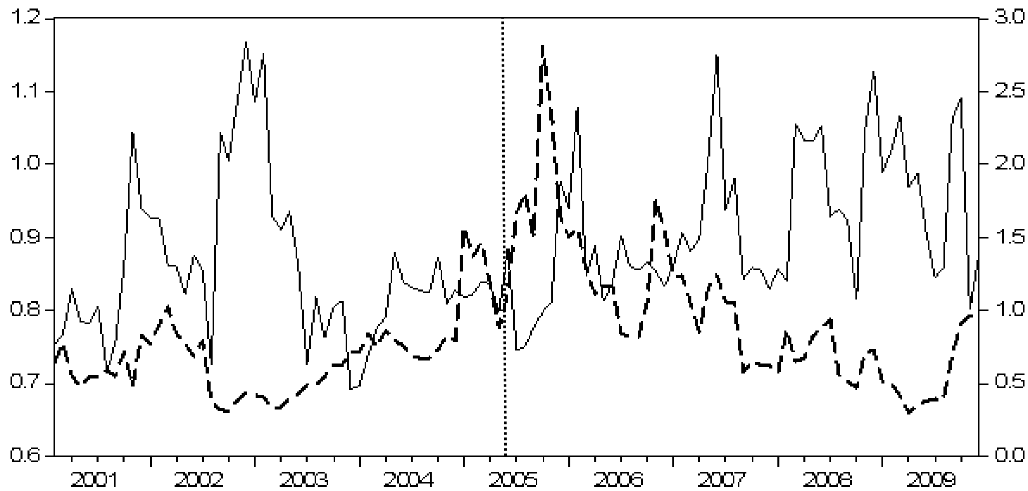


Notes: This figure shows the returns for the FTSE4Good index on the ordinate axis and time on the abscissa axis. The sample spans from January 2001 to December 2009.

Figure 4.4 Estimated Rolling Betas for the Online Gambling and Socially Responsible Portfolios

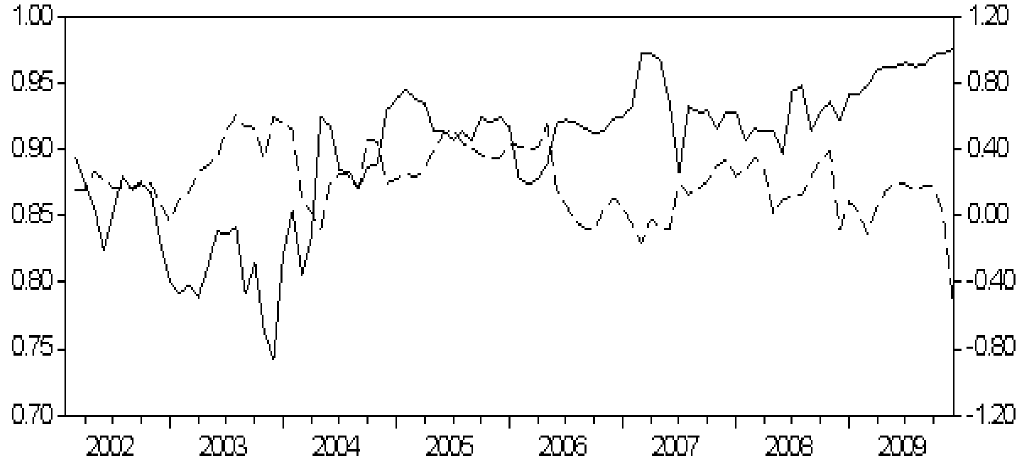
Notes: This figure shows the rolling betas for the FTSE4Good index (the equally-weighted internet gambling portfolio) on the left (right) ordinate axis and time on the abscissa axis. Solid line represents the rolling betas of the FTSE4Good index. The sample spans from January 2003 to December 2009. The rolling betas are computed using a rolling window of 24 months.

Figure 4.5 Estimated Conditional Betas for the Online Gambling and Socially Responsible Portfolios



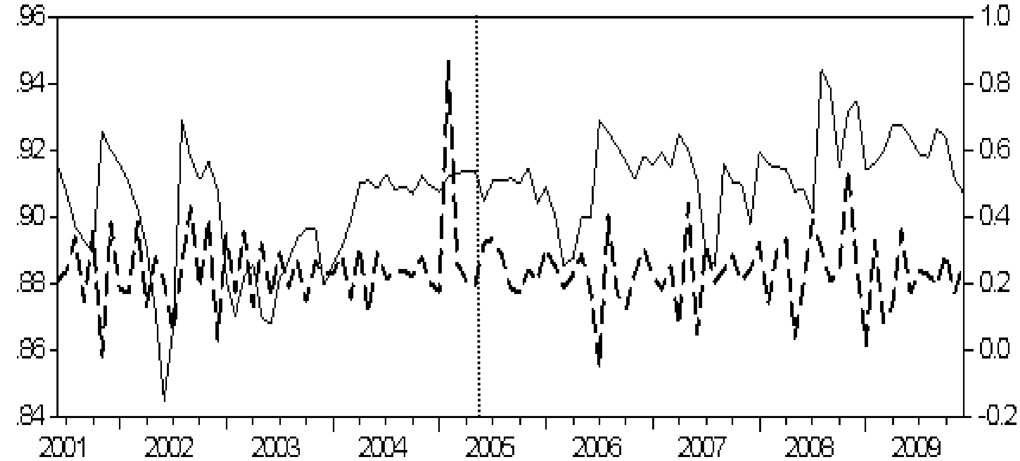
Notes: This figure shows the conditional betas of the FTSE4Good index (the equally-weighted internet gambling portfolio) on the left (right) ordinate axis and time on the abscissa axis. Solid line represents the conditional betas of the FTSE4Good index. The dashed vertical line represents the passage of the Gambling Act 2005. The sample spans from January 2001 to December 2009.

Figure 4.6 Estimated Rolling Correlations for the Online Gambling and Socially Responsible Portfolios



Notes: This figure shows the rolling correlations of the FTSE4Good index (the equally-weighted internet gambling portfolio) with the FTSE All-share index on the left (right) ordinate axis and time on the abscissa axis. Solid line represents the rolling correlations of the FTSE4Good index rolling with the FTSE All-share index. The sample spans from January 2001 to December 2009. The correlation is computed using a rolling window of 12 months.

Figure 4.7 Estimated Conditional Correlations for the Online Gambling and Socially Responsible Portfolios



Notes: This figure shows the conditional correlations of the FTSE4Good index (the equally-weighted internet gambling portfolio) with the FTSE All-share index on the left (right) ordinate axis and time on the abscissa axis. Solid line represents the FTSE4Good index conditional correlation with the FTSE All-share index. The dashed vertical line represents the passage of the Gambling Act 2005. The sample spans from January 2001 to December 2009.

Table 4.1 Descriptive Statistics

	IGAM	*FTSE4G*	*MKT*	*RF*
Mean	-0.303	-0.192	-0.084	0.340
Maximum	39.714	9.222	10.369	0.488
Minimum	-51.021	-14.450	-13.497	0.030
Std. Dev.	14.305	4.616	4.608	0.119
Skewness	-0.235	-0.805	-0.722	-1.519
Kurtosis	4.879	3.561	3.750	4.522
Jarque-Bera	16.726	12.961	11.816	51.460
Probability	0.000	0.002	0.003	0.000
Observations	107	107	107	107

Notes: Table 4.1 reports the descriptive statistics for the online gambling portfolio, the FTSE4G portfolio, the stock market, and the risk-free rate. Results are shown for the entire sample period. The sample spans from January 2001 to December 2009. *IGAM* is the monthly return on the equally-weighted online gambling portfolio. *MKT* is the monthly return on the value-weighted FTSE All-Share index. *FTSE4G* is the monthly return on the FTSE4Good index. *RF* is the 3-month UK Treasury bill rate expressed as a monthly rate.

Table 4.2 Unconditional and Conditional Performance Measures and Betas

	IGAM	*FTSE4G*	*MKT*
Unconditional Sharpe ratio	-0.044	-0.115	-0.092
Conditional Sharpe ratio	-0.045	-0.125	-0.100
Unconditional Treynor ratio	-1.040	-0.578	
Conditional Treynor ratio	-0.767	-0.599	
Jensen's alpha	-0.381	-0.142*	
t-stat	-0.258	-1.762	
Beta	0.618***	0.919***	
t-stat	2.275	24.628	
Conditional beta average	0.839***	0.888***	
t-stat	20.056	84.332	

Notes: Table 4.2 reports the unconditional and conditional Sharpe ratios for the equally-weighted internet gambling portfolio (*IGAM*), the FTSE4Good index (*FTSE4G*) and the value-weighted FTSE All-Share index (*MKT*). In addition, the unconditional and conditional Treynor ratios for the equally-weighted internet gambling portfolio (*IGAM*) and FTSE4Good index (*FTSE4G*). Jensen's alpha and beta—the intercept and slope from a CAPM time-series regression—are shown for *IGAM* and *FTSE4G*. Furthermore, the conditional beta average for *IGAM* and *FTSE4G* is shown. Results are shown for the entire sample period, which spans from January 2001 to December 2009. *** 1%; ** 5%; * 10% significance.

Table 4.3 Jobson and Korkie Tests

	(*IGAM*, *MKT*)	(*FTSE4G*, *MKT*)	(*IGAM*, *FTSE4G*)
Test statistic	-0.384	0.605	-0.589

Notes: Table 4.3 reports the *z* test statistic of pair-wise comparisons of Sharpe ratios using the Jobson and Korkie test. Under the null hypothesis of the test, Sharpe ratios are statistically equal. (*IGAM*, *MKT*) is the pair-wise comparison of Sharpe ratios between the equally-weighted internet gambling portfolio (*IGAM*) and the value-weighted FTSE All-Share index (*MKT*). (*FTSE4G*, *MKT*) is the pair-wise comparison of Sharpe ratios between the FTSE4Good index (*FTSE4G*) and the value-weighted FTSE All-Share index (*MKT*). (*IGAM*, *FTSE4G*) is the pair-wise comparison of Sharpe ratios between the equally-weighted internet gambling portfolio (*IGAM*) and the FTSE4Good index (*FTSE4G*). Results are shown for the entire sample period. The sample spans from January 2001 to December 2009. *** 1%; ** 5%; * 10% significance.

Table 4.4 Alternative Sharpe Ratios

	Ferruz and Sarto Sharpe ratio	Israelsen Sharpe ratio	Normalized Sharpe ratio
FTSE4G	-0.122	-0.053	0.003
IGAM	-0.062	-9.211	-0.019
MKT	-0.053	-1.950	

Notes: Table 4.4 reports the alternative Sharpe ratios for the equally-weighted internet gambling portfolio (*IGAM*), the FTSE4Good index (*FTSE4G*) and the value-weighted FTSE All-Share index (*MKT*). Results are shown for the entire sample period. The sample spans from January 2001 to December 2009.

Table 4.5 Descriptive Statistics for Rolling and Conditional Betas

	FTSE4G rolling beta	*IGAM* rolling beta	*FTSE4G* conditional beta	*IGAM* conditional beta
Mean	0.906	1.082	0.888	0.839
Maximum	1.049	3.509	1.168	2.812
Minimum	0.742	-0.046	0.692	0.294
Std. Dev.	0.057	0.859	0.109	0.433
Skewness	-0.302	1.028	0.682	1.660
Kurtosis	3.114	2.790	2.817	6.944
Jarque-Bera	1.308	14.782	8.454	118.488
Probability	0.520	0.001	0.015	0.000
Observations	83	83	107	107

Notes: Table 4.5 reports the descriptive statistics for the betas of the online gambling portfolio and the *FTSE4G* portfolio. The following equation is estimated to calculate the rolling betas: $\left(R_{p,t}-R_{f,t}\right)=\alpha_p+\beta_p\left(R_{m,t}-R_{f,t}\right)+\varepsilon_{p,t}$, where $R_{p,t}$ represents the return on the pth portfolio at time t, $R_{f,t}$ the risk-free rate, $\varepsilon_{p,t}$ the unobservable stochastic white-noise process. In addition, beta for the pth portfolio (β_p) and Jensen's alpha ($\boldsymbol{\alpha}_p$) are the parameter estimates. For the rolling betas, the sample spans from January 2003 to December 2009. The rolling betas are computed using a 24 month rolling window. The conditional betas are estimated as follows, $\beta_{p,t}=\frac{cov(R_{p,t},R_{m,t})}{var(R_{m,t})}$, where $cov\left(R_{p,t},R_{m,t}\right)$ is the conditional covariance between the relevant portfolio and the market and $var(R_{m,t})$ is the conditional variance of the market. For the conditional beta, the sample spans from January 2001 to December 2009. *IGAM* is the monthly return on the equally-weighted internet gambling portfolio. *FTSE4G* is the monthly return on the FTSE4Good index.

Table 4.6 Correlation Matrix of the Estimated Conditional Betas

	FTSE4G conditional beta	*IGAM* conditional beta
FTSE4G conditional beta	1.00	
t-statistic	--	
IGAM conditional beta	-0.17	1.00
t-statistic	(-1.80)*	--

Notes: Table 4.6 shows the correlation matrix of the estimated conditional betas for the FTSE4Good index (*FTSE4G*) and the equally-weighted internet gambling portfolio (*IGAM*). Results are shown for the entire sample period. The sample spans from January 2001 to December 2009. *** 1%; ** 5%; * 10% significance.

Table 4.7 Descriptive Statistics for Rolling and Conditional Correlations

	FTSE4G rolling correlation	IGAM rolling correlation	FTSE4G conditional correlation	IGAM conditional correlation
Mean	0.899	0.212	0.907	0.238
Median	0.914	0.200	0.911	0.231
Maximum	0.975	0.606	0.944	0.863
Minimum	0.741	-0.510	0.845	-0.051
Std. Dev.	0.053	0.198	0.017	0.117
Skewness	-0.862	-0.327	-0.901	1.318
Kurtosis	3.134	3.682	4.213	9.985
Jarque-Bera	11.718	3.499	20.258	239.240
Probability	0.003	0.174	0.000	0.000
Observations	94	94	103	103

Notes: Table 4.7 reports the descriptive statistics of the estimated correlations between the FTSE all share index and *IGAM* (*FTSE4G*). *IGAM* is the monthly return on the equally-weighted internet gambling portfolio. *FTSE4G* is the monthly return on the FTSE4Good index. The following equation is used to estimate the rolling correlations: $\hat{\rho}_{12,t} = \frac{\sum_{s=t-n}^{t} r_{1s} r_{2s}}{\sqrt{(\sum_{s=t-n}^{t} r_{1,s}^2)(\sum_{s=t-n}^{t} r_{2,s}^2)}}$, where $\hat{\rho}_{12,t}$ is the estimated correlation at time *t*. For the rolling correlations, the sample spans from January 2002 to December 2009. The rolling correlations are computed using a rolling window of 12 months. Conditional correlations are estimated using of Engle's (2002) dynamic conditional correlation model. The time-varying correlation matrix is of the following form:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where Q_t^* is a diagonal matrix with the square root of the diagonal elements of the covariance matrix Q_t. The evolution of the conditional covariance matrix is modeled as follows: $Q_t = (1 - a - b)\bar{Q} + a(\Xi_{t-1}\Xi_{t-1}') + bQ_{t-1}$, where a and b are parameters to be estimated. Furthermore, $\bar{Q}$ is an unconditional covariance matrix, Ξ_{t-1} is the lagged residual vector, and Q_{t-1} is the lagged covariance matrix. For the conditional correlation, the sample spans from January 2001 to December 2009.

CHAPTER V

SUMMARY AND CONCLUSIONS

A growing body of literature focuses on the relationship between investor sentiment and asset prices. The literature, for the most part, shows that investor sentiment has an influence on asset prices (Hirshleifer, 2001). Despite these findings, previous sin stock studies have failed to examine the possible link between investor sentiment and sin stock returns (see, e.g., Perez Liston and Soydemir, 2010; Hong and Kacperczyk, 2009; Fabozzi, MA, and Oliphant, 2008; Salaber, 2007a). Chapter 3 of this dissertation contributes to the literature by first examining the role of individual and institutional investor sentiment in determining *pure sin* returns. To examine this relation, this study splits both sentiment measures into their respective rational and irrational components. Moreover, unlike previous studies, the returns of the sin portfolio are dichotomized into market-based and pure sin components. Next, this study examines the volatility of the sin portfolio using a GARCH framework and tests whether volatility occurs in clusters, if a leverage effect is present, and if volatility impacts sin returns. Furthermore, the relation of investor sentiment with sin stocks' volatility and excess returns is examined. Finally, in an asset-pricing framework, the impact of both types of sentiments on sin returns is quantified. This study also examines whether the introduction of investor sentiment explains the overperformance of sin stocks found in previous empirical studies.

The generalized impulse response functions from the vector autoregressive model indicate that positive shocks in both rational-based individual and institutional investor sentiments have a significant and positive effect on *pure sin* returns. In contrast to the S&P 500 and comparables portfolios, the pure sin returns exhibit a weaker positive response to both institutional and individual rational sentiment shocks. The pure sin series exhibits a positive but insignificant response to shocks in irrational-based sentiment. In general, when compared to the S&P 500 and the comparables portfolio, the sin portfolio is less sensitive to irrational and rational waves of investor sentiment.

The results from the GARCH modeling indicate changes in both types of investor sentiment positively influence sin stocks returns. Furthermore, we find evidence of volatility clustering and a leverage effect. The results also show that sin stock returns are positively related to its respective volatility, but only when individual sentiment is included in the model. Moreover, noise trader risk significantly impacts the formation of volatility for such stocks; however, the direction and magnitude depend whether individual or institutional investor sentiment is used. Thus, changes in investor sentiment lead to changes in volatility.

The results from all three sentiments-augmented asset pricing models imply that both individual and institutional investor sentiments are priced factors in sin stock returns. The evidence suggests a consistent positive contemporaneous relationship between sin stock returns and both types of investor sentiment. More importantly, after controlling for the effects of investor sentiment on the sin portfolio, the abnormal returns found in previous studies vanish.

This suggests that the abnormal performance found in previous studies might be due to model misspecification, not to norm-neglect, as posited.

The second part of this dissertation examines the financial performance, correlations, and market sensitivities of an internet gambling portfolio relative to both the market and socially responsible portfolios. The results provide important and interesting findings. First, financial performance measures--that account for periods where excess returns are negative--indicate that the online gambling portfolio underperforms relative to both the market and socially responsible portfolios. Thus, it appears that there is a cost, in terms of risk and return, to reducing the investable universe to online gambling stocks. This finding contrasts to those presented in Chapter 3, where the sin portfolio outperforms the market when investor sentiment is not included. Second, the evidence suggests that online gambling beta is time-varying and that it increases considerably around the passage of the Gambling Act 2005. As a result, important gambling legislative events might lead to increased portfolio risk for an investor whose portfolio includes online gambling stocks. In addition, the results suggest that the beta for the online gambling portfolio is less that one, indicating defensiveness towards the market portfolio, which is consistent with the findings from Chapter 3. There the sin portfolio also had a beta of less one. Therefore, the evidence suggests that investors seeking protection from the market should invest in online gambling stocks. Third, results from estimating a dynamic conditional correlation model suggest that the conditional correlation of the online gambling portfolio with the market portfolio increases during the passage of the Gambling Act 2005. This increased correlation, during legislative events, leads to a loss in diversification from holding an online gambling portfolio.

Overall, this dissertation bridges the gap on how investor sentiment affects sin stock returns and volatility. At the same time, it also provides evidence on the financial performance, betas, and correlations for the relatively new online gambling stocks.

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Mr. Daniel R. Perez is currently working at Prairie View A&M University as an Assistant Professor of Finance. In 2004, Mr. Perez received his Bachelor of Business Administration, in Finance, from The University of Texas-Pan American. Two years later, he received from the same university his Master of Business Administration (MBA) with a concentration in management. After completion of his MBA, Mr. Perez began work on his Ph.D. in Business Administration, with an emphasis in Finance at the same institution. He graduated from the program in May of 2011.

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