POSITIVE MOOD, RISK ATTITUDES, AND INVESTMENT DECISIONS: FIELD EVIDENCE FROM COMEDY MOVIE ATTENDANCE IN THE U.S.

-preliminary draft-

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Abstract

Positive mood has been repeatedly shown to affect risk attitudes in laboratory settings, where subjects' exposure to movie clips is among the most widely used and effective mood-induction procedures. Yet, conflicting lab results about the estimated sign of the mood effect have led researchers to formulate two alternative theories. The *affect infusion model* (AIM) argues that happy moods foster risk-prone behavior, whereas the *mood-maintenance hypothesis* (MMH) takes the opposite stance. In this paper I test the predictions of these two theories using real-world financial data and focusing on the same mood-shifting mechanism commonly employed in lab studies. More specifically, I exploit the time-series variation in the domestic theatrical release of comedy movies as a natural experiment for testing the impact that happy mood (proxied by weekend comedy movie attendance) has on investment in risky assets (proxied by the performance of the U.S. stock market on the following Monday). My hypothesis rests upon the evidence that individual investors are more likely to ponder trading decisions during the weekend and trade on Mondays. To control for unobserved factors that may contemporaneously affect movie attendance and equity returns, I employ the percentage of theater screens dedicated to the comedy genre as an instrument. Using a sample of data from 1995 to 2010, I estimate that an increase in comedy attendance on a given weekend is followed by a decrease in equity returns on the subsequent Monday, which supports the MMH.

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1. Introduction

The role that mood plays in decision making under risk has been investigated in lab experiments and using field data.[1] The findings consistently show that mood can influence people' risk attitudes/perceptions and, in turn, their choices. Yet, there seems to exist a clear gap between the methodologies that have been employed in the lab and the approaches that have been followed when dealing with data from the field. In the lab, in order to induce a mood shift in their subjects and study their risk attitude reactions, researchers typically use such techniques as showing short movies clips, playing sounds/music, asking subjects to read short stories/statements, and giving subjects small gifts (e.g. Johnson and Tversky, 1983; Au et al., 2003; Chou et al., 2007; Isen and Patrick, 1983). Field studies focusing on mood, risky investment decisions and aggregate stock market outcomes, on the other hand, generally assume that some environmental factor (e.g. sunshine, hours of daylight, sports results, aviation disasters, etc) is responsible for generating mood changes in a large fraction of the investor population, which in turn translate into changes in risk aversion and/or optimism and affect portfolio choices (e.g. Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Edmans et al., 2007; Kaplanski and Levy, 2009). It appears, as such, that there is no exact overlap between these two streams of literature: the existing field studies are not directly rooted into some previous lab experiment addressing the same mood-shifting mechanism and, symmetrically, the findings of existing lab experiments involving certain mood-induction procedures lack corroboration from real-world data. For instance, happy and sad movie clips have been shown to affect individuals' emotional states, risk attitudes, and decisions under risk in the lab. Does the same apply when people watch movies in their natural environment and are called upon making real-life risky decisions? The goal of the present paper is to fill this gap by exporting a popular mood-manipulation mechanism (i.e. exposure to funny movie clips) from the lab to the realm of field research. More specifically, in what follows I investigate whether fluctuations in domestic comedy movie attendance (assuming that exposure to a comedy movie represents a source of mood enhancement) have an impact on the marginal American investor's risk attitudes, investment decisions and, as a result, on aggregate U.S. stock returns.

A second important contribution of this study is that, using real-world data, I test the predictions of two competing theories originated from the lab. Conflicting lab results about the

[1] Psychologists typically make a distinction among the concepts of affect, mood and emotion (e.g. Grable and Roszkowski, 2008), yet in the behavioral finance literature it is common to use such terms interchangeably. Here I will follow the latter approach.

influence of positive affect on risk propensity have led experimental researchers to formulate two opposite hypotheses. According to the so-called *affect infusion model* (AIM), positive mood fosters risk-prone behavior. This may happen because happy moods cue positive memories and lead to a more favorable assessment of the environment (e.g. Forgas and Bower, 1987; Chou et al., 2007); also, people experiencing a happy emotional state may tend to rely more heavily on heuristic information processing, which may contribute to a risk-prone response (Forgas, 1998; Leith and Baumeister, 1996). The *mood-maintenance hypothesis* (MMH), instead, maintains that people in good moods tend to behave more cautiously in risky situations, especially when potential losses are real and salient, as they try to protect their current good emotional state (e.g. Isen and Patrick, 1983; Isen and Geva, 1987).[2] Which effect dominates when real risky decisions are involved and the monetary stakes are considerably high (as it occurs in financial markets)? In order to provide an empirical evaluation of these two alternative interpretations, as previously mentioned, here I focus on the relationship between weekend comedy movie attendance and Monday's stock market behavior from December 9, 1994 through May 30, 2010. Based on the AIM, the wave of positive mood that allegedly follows an increase in weekend comedy attendance should encourage risk taking across the population, thus boosting the demand for risky assets and increasing stock returns on the following Monday. According to the MMH, instead, the same event should promote risk avoidance, depress the demand for risky assets, and lower equity returns. Both channels rest upon the evidence that individual investors tend to contemplate trading decisions during the weekend and trade more on Mondays (e.g. Venezia and Shapira, 2007).

The results of my empirical analysis are consistent with the hypothesis that changes in comedy movie attendance generate sizable mood fluctuations across the population and, more in detail, the data lend support to the MMH. Starting off my investigation with a naïve OLS regression that ignores any endogeneity issues, what I find is that, after controlling for overall movie attendance (i.e. regardless of movie genre), seasonal dynamics, and some other factors typically considered in the behavioral finance literature, the size of the audience for comedy movies during the weekend is negatively correlated to the following Monday's stock returns (as measured by CRSP data). More in detail, the marginal effect of a 10% (one standard deviation) increase in the number of comedy viewers is estimated to be approximately -0.01% (-0.07%), all else equal. This effect is statistically significant and is consistent with a reduced demand for stocks, which in turn is

[2] To the best of my knowledge, the stream of literature concerning the MMH has been almost entirely overlooked so far in the behavioral finance arena, while it has gained much attention from psychologists. As such, an additional contribution of this paper consists in bringing this important area of investigation to the attention of finance experts.

consistent with domestic investors being less willing to take risks when experiencing a movie-induced positive mood.

The analysis becomes more complex once one recognizes that comedy movie attendance is likely to be endogenous in this setting. While in the lab subjects are randomly assigned to different mood conditions (i.e. happy, sad or neutral movie clips), in the natural environment the movie genre is optimally chosen by the consumers.[3] The sorting of moviegoers into different movie genres may be influenced by their current mood states (Zillman and Bryant, 1985; Helregel and Weaver, 1989; Strizhakova and Krcmar, 2007), which may be affected by some personal life events, some purely environmental factors (e.g. rain), and some economic/political events/news (e.g. a terrorist attack). In other words, there may be some unobserved factors that contemporaneously affect comedy movie attendance on a given weekend and the behavior of the stock market on the following Monday. For instance, if some notably negative economic news hits the market during the weekend, people may be induced to seek refuge from reality in comedy hits like *Bruce Almighty* and *The Simpsons Movie*. To address this issue I follow two strategies in the spirit of Dahl and DellaVigna (2009). First, I add to the regression equation three sets of controls that measure some features of the physical environment that over the weekend could potentially affect people's moods, movie choices, and subsequent investments in risky assets. Adding these controls does not alter the previous results. Second, I instrument for weekend comedy movie attendance using the percentage of movie theaters in which a comedy is playing. Since the number of screens dedicated to a given movie is finalized one or two weeks in advance (Moretti, 2008; Dahl and DellaVigna, 2009), this instrument should clean the estimates of short-term shocks that may influence both comedy movie attendance on weekend t and equity returns on the following Monday. Instrumenting renders the marginal effect of comedy movie attendance even larger (in absolute value) compared to the baseline model. According to the IV model that I employ, a 10% (one standard deviation) increase in comedy attendance on a given weekend is estimated to be followed by roughly a 0.02% (0.13%) decrease in stock returns on the subsequent Monday, all else equal. This appears to be an economically relevant effect, especially when compared to similar studies in the literature. The use of alternative instruments produces very similar (and statistically significant) results.

Previous research has shown that violent media (e.g. violent movies) and frightening entertainment (e.g. horror movies) may foster reactions that encompass aggressive behavior, fear,

[3] In the natural environment not only do people choose between alternative movie genres, but they also choose between going to the movies and alternative leisure activities. By construction, the latter is not possible in lab experiments.

and anxiety. In order to control for the influence that violent and thrill-inducing movie content may have on viewers' emotional states and risk attitudes, I also add to the model two covariates that measure the number of weekend moviegoers exposed to highly violent movie content or to thriller/suspense movies. What I find is that the effects of these two additional explanatory variables exhibit the expected sign; when using an IV specification, I also provide some limited evidence of a significantly positive impact of exposure to violent content on risk taking propensity, which is in line with the results documented in the literature. Nevertheless, the previous results concerning the effect of comedy movie attendance are not affected.

To show that the findings are not driven by liquidity effects or other market frictions, I follow Tetlock (2007) and I include in the model a set of lagged squared return residuals and NYSE detrended trading volumes. The results are also robust to the inclusion of a set of holiday controls, TV audience controls, and business cycle proxies, and do not appear to be driven by outliers. Last, I verify that the findings are not sensitive to some alternative classifications of movies into the comedy genre. In order to provide more evidence on the link of causality, in the last portion of my analysis I focus on the cross section of stock returns. According to the analyses carried out by Baker and Wurgler, (2006) and Kumar (2009), investor sentiment appears to exert a larger influence on the pricing of stocks that feature a high valuation uncertainty and that are more difficult to arbitrage. Based on these insights, one would expect to observe a stronger impact of mood on the pricing of (among others) high-volatility stocks, high-beta stocks, extreme-growth stocks, distressed stocks, and small-cap stocks. Using CRSP returns calculated on standard deviation-based and beta-based deciles I find that, indeed, the marginal effect of comedy attendance is estimated to be increasing (in absolute value) in the beta and volatility of stocks. Moreover, using Fama and French (1992) 10 value-weighted portfolios constructed by industry, I document that the effect of interest is stronger for less stable industries (*HiTech*, *Durbl*) than for stable ones (*Nodur*, *Utils*). When examining the Fama and French (1992) portfolios sorted by size and by book-to-market ratio (whose low and high values proxy for extreme-growth and distressed stocks, respectively), instead, I do not observe any statistically significant differential effect.

The rest of the paper is organized as follows. Section 2 presents the lab and field evidence on the relationship between positive affect and risk-taking behavior, discusses the MMH and AIM, and highlights some limitations of lab experiments. Section 3 puts forward the behavioral hypotheses that will be tested. Section 4 describes the data and section 5 contains the empirical analysis and a battery of robustness checks. Section 6 concludes.

2. Positive Affect and Risk Attitudes

2.1. Risk Perception

Risk taking can be investigated along several dimensions, including "outcome uncertainty, outcome expectation, outcome potential, personal involvement, and perceived safety and control" (Chou et al. 2007). Laboratory studies have consistently documented that happy moods tend to reduce the *perception* of risk, at least when subjects are asked to evaluate the likelihood of some hypothetical future events or scenarios. Johnson and Tversky (1983) manipulate their subjects' moods by asking them to read some short stories and find evidence that positive mood causes a global decrease in the judged frequency of a set of hypothetical life threatening risks. Wright and Bower (1992), using a mood-induction procedure based on hypnosis, show that individuals in a positive mood tend to overestimate the likelihood of hypothetical (personal and social) positive events and underestimate the probability of adverse events. Similar findings are documented by Constans and Matthews (1993), who manipulate their subjects' moods by asking them to imagine a series of either positive or negative life events, and MacLeod and Campbell (1992), whose subjects read short descriptions of pleasant or unpleasant events. Wegener et al. (1994) expose their subjects to happy or sad videotapes and find that, when individuals are called upon assessing the merits of a given message argument, "positive mood [leads] to marginally greater perceived likelihood of positive consequences but to lower likelihood of negative consequences as compared to negative mood". Nygren et al. (1996) induce positive mood in their treatment group by giving them a free bag of candy, and observe that participants in a positive mood state tend to overestimate the probability of winning when presented with a series of three-outcome gambles.

2.2. Risk Taking Propensity

The evidence is much more controversial, though, when one considers the studies in which, rather than having to estimate event probabilities, subjects are asked to make actual (or hypothetical) decisions under risk. In their experiment, Isen and Patrick (1983) trigger a positive mood response by giving student subjects in the treatment group a free gift certificate and find that, when actual credit hours are at stake, only in the case of low-risk bets happy mood fosters risk taking in a game of roulette; when high-risk bets are considered, instead, individuals in a positive mood tend to be more risk averse than controls. Similar results are obtained by Isen and Geva (1987) using as a mood-induction device a free bag of candy. Arkes at al. (1988), also using the latter approach, observe that positive-affect subjects are willing to pay more for hypothetical lottery tickets (increased risk taking propensity) but are also willing to pay more to buy insurance against hypothetical losses, especially when the potential loss is large (increased risk aversion). Using a virtual foreign exchange market and a mood-induction procedure based on a combination of performance feedback and pleasant/unpleasant background music, Au et al. (2003) find that traders in a good mood display a more risk-prone behavior than controls and bad-mood traders. Analogously, in Chou et al. (2007)'s experiment individuals watch happy, neutral, or sad movie clips and subsequently respond to some hypothetical everyday life dilemmas, revealing that happy mood appears to promote risk propensity under such circumstances. More recently, Trujillo et al. (2008) expose their subjects to happy, neutral, or negative facial expressions, and document that positive-mood individuals are more likely to make risky choices when confronting hypothetical gambling tasks. On the opposite side, both Isen et al. (1988) and Nygren et al. (1996), after eliciting a positive mood response by giving their student subjects a free bag of candy, find that, in gambling tasks where actual credit hours are at stake, positive-mood individuals exhibit more conservatism and a preference for avoiding losses, especially when a large loss is possible. Interestingly, this decrease in risk tolerance takes place even if positive-mood participants appear to overestimate the probabilities of winning (Nygren et al., 1996). Similarly, Mittal and Ross (1998) document that, though subjects in a positive mood are more likely to interpret some hypothetical strategic marketing issues as an opportunity rather than a threat, they diplay a lower level of risk propensity when it comes to investing money in some hypothetical action plans in response to the strategic issue. More recently, Lin et al. (2006) and Heath (2007) expose their subjects to happy or sad movie clips and subsequently present them with some hypothetical everyday life dilemmas and hypothetical investment decisions, respectively; both teams observe that participants in a happy mood display more conservatism and risk aversion than the controls. With regard to natural (i.e. unmanipulated) mood, in a survey of adults who volunteered to answer a questionnaire of the type typically employed by financial advisors, Grable and Roszkowski (2008) find that people currently experiencing a happy mood display a higher level of financial risk tolerance when confronted with hypothetical investment decisions than people in a neutral mood. Analogously, Gabbi and Zanotti (2010), using a virtual stock market game and tracking their subjects' mood states through daily surveys over a six-week period, find some evidence that happy individuals are more likely to enter long positions and increase their financial leverage.

Another stream of literature that is relevant for the present study is the one that relates the performance of the stock market (which is intended as a proxy for people's willingness to invest in risky assets) to the dynamics of some pervasive environmental stimuli (which are assumed to generate widespread mood shifts across the population of investors). In a highly cited study, Hirshleifer and Shumway (2003) investigate the relationship between morning sunshine in the city hosting a stock exchange and daily returns on the corresponding market index in a sample of 26 countries. The authors document a positive correlation between the two variables, which they interpret as evidence that positive mood (allegedly triggered by sunshine) leads people to be more risk-prone and/or to evaluate future prospects more optimistically. Edmans et al. (2007), instead, examine the impact of international soccer results on the performance of the participant countries' stock markets and provide evidence that a loss (by supposedly causing a wave of mood deterioration across the population) reduces next-day stock returns; yet, they find no statistical evidence of an opposite effect after wins. Conversely, Ashton et al. (2003), focusing on the UK stock market, also find some evidence of positive abnormal returns after wins of the England national team; this would suggest that happy moods may encourage investment in risky assets. Several other studies have analyzed negative mood triggers and a number of them have documented a mood-congruent reaction of the relevant stock market (e.g. Kamstra et al., 2003; Yuan et al., 2006; Kaplanski and Levy, 2009).

2.3. Affect Infusion Model vs. Mood Maintenance Hypothesis

Two different theories have emerged in an attempt to explain the empirical results described in the previous two sections. The AIM proposes that positive mood increases risk taking (Forgas, 1995). This model is supported by two complementary lines of research; according to the *mood-as-information* model proposed by Schwarz and Clore (1983), the way people make judgments is partially affected by how they feel and, more specifically, individuals are prone to make mood-congruent assessments. In other words, people experiencing a positive mood are expected to evaluate the environment more favorably (Bower, 1981), which encourages proactive behavior. This may result from the fact that positive affect facilitates the recall of positive material in memory and thus generates judgment patterns in line with positive memories (Isen et al., 1978; Forgas and Bower, 1987). A second line of research on heuristic processing argues that people in a positive mood are likely to use a "processing strategy that relies heavily on the use of simple heuristics, and that is characterized by a lack of logical consistency and little attention to detail"

(Schwarz and Bless, 1991). Individuals in a positive mood are therefore less likely to be aware of the potential negative consequences of their decisions, and a lack of careful and rational thought may intensify their risk-prone responses (Leith and Baumeister, 1996; Forgas, 1998). On the opposite side, the MMH maintains that, though positive affect may improve expectations, risk estimates, and even make people more brave in some circumstances, it is reasonable to expect that individuals are highly protective of their good mood states (Isen and Patrick, 1983). For this reason, when making decisions under risk that may endanger their good moods, people in a positive affect state are likely to behave cautiously and avoid taking risks (Isen and Geva, 1987; Arkes et al., 1988).

Several possible reconciliations of the available findings and of the two theories have been advanced. Isen and Patrick (1983) argue that the results put forward in the literature are not necessarily in contradiction with one another, as different studies focus on (or control for) different aspects of the risky decision: e.g. expectations regarding the possible outcomes, perception of costs and rewards, and willingness to take risks. According to Forgas (1995), the AIM is likely to dominate in contexts that require substantial information processing and an accurate evaluation of complex issues, whereas the MMH may be dominant when people have a strong impetus to attain a particular outcome. Other authors suggest that the MMH is likely to dominate in decision frames where possible losses are real and salient (Isen and Patrick, 1983; Arkes et al., 1988), the stakes are high (Isen and Geva, 1987), and actual large losses may occur (Nygren et al., 1996). Similarly, according to Andrade and Cohen (2007), positive affect is likely to lead to risk-prone behaviors when there are no salient threats in the decision frame, but when some "environmental cues signal threats" then it is likely to encourage "negative mood avoidance through risk-averse behaviors". Given that investing in financial markets requires complex information processing (at least in principle) and also involves large potential losses, the theory alone does not seem to provide enough guidance as to which of the two effects one should expect to dominate in such a context.

2.4. Limitations of Lab Studies and Existing Field Studies

A number of factors suggest that it is important to complement the lab experiments discussed in sections 2.1 and 2.2 with large-scale field investigations. Here I call attention to the fact that (1) a large fraction of the above-mentioned lab studies involves hypothetical risks, which may be treated differently from real risks by subjects (Slovic, 1969); (2) experimental decision tasks are often unrealistic, as researchers frequently present subjects with lottery-type questions or other overly simplified gambling tasks (Bromiley and Curly, 1992); (3) when called upon making a decision, subjects are often given precise information on (e.g.) the possible outcomes and associated probabilities, whereas in the real world these factors have to be subjectively estimated; (4) in the experiments in which actual bets are made, subjects always receive a free initial endowment (e.g. poker chips, credit hours), which might generate a sort of "house money effect" (Thaler and Johnson, 1990) and bias their ensuing behavior; (5) even if some experiments require subjects to make actual bets, thus exposing them to real potential losses, they all involve small scale decisions in which the real stakes are not high; (6) lab research may implicitly induce individuals to pay more attention to their emotions or to behave in line with perceived experimental demand (Mayer et al., 1992); (7) the vast majority of lab experiments employs student subjects, and the sample often consists of psychology undergraduates. The latter group may be more open to their moods for a variety of reasons, and college students overall "are likely to have less-crystallized attitudes, less-formulated senses of self, stronger cognitive skills, stronger tendencies to comply with authority, and more unstable peer group relationships" (Sears, 1986). Not surprisingly, in a meta-analysis of studies that employ student and nonstudent subjects, Peterson (2001) finds that the direction and/or the magnitude of the effects documented in studies that employ the former frequently differ from the ones obtained when using the latter.

At the same time, the existing field studies on the relationship between mood and investment in risky assets (e.g. Hirshleifer and Shumway, 2003; Edmans et al., 2007; Kaplanski and Levy, 2009), though shedding light on the issue, do not seem to effectively bridge between experimental and observational data, as they do not focus on the same mood-shifting mechanisms that have been analyzed by experimental researchers. One of the advantages of the present study is that it allows a direct comparison between the results obtained in the lab when exposing subjects to happy movie clips and the results arising from the field where individuals are exposed to comedy movies in their natural environment.

3. Hypotheses under Scrutiny

My null hypothesis follows from the classical finance paradigm, according to which individuals are rational and markets are efficient, so that equity prices should be unaffected by the dynamics of domestic comedy audiences (provided the direct economic effects of movie attendance are controlled for) and people's moods. The alternative hypothesis asserts that an increase in comedy movie admissions during the weekend generates a corresponding wave of mood enhancement across the population. In turn, the latter factor may influence the marginal investor's risk taking behavior and the investment decisions she assesses over the weekend. Given that actual trades can only be implemented when the market reopens, this chain of events will ultimately affect demand in the stock market and equilibrium prices on the following Monday. Based on the literature discussed in the previous sections, two distinct alternative hypotheses can be advanced with regard to the expected sign of this movie-induced mood effect. According to the AIM, positive mood leads to a rise in risk propensity, so that

> *H1a: an exogenous increase in the number of people that are exposed to comedies should cause the net demand for risky assets to rise and increase stock returns, all else equal.*

On the other hand, the MMH predicts that positive mood leads individuals to behave more cautiously in order to protect their current emotional states, which implies that

> *H1b: an exogenous increase in the number of people that are exposed to comedies should cause the net demand for risky assets to fall and reduce stock returns, all else equal.*

The existence of this movie-induced mood effect relies on several key pieces of evidence: (i) moviegoing is a highly popular leisure activity in the United States; according to UNESCO statistics, between 1995 and 2006 the U.S. constantly ranked among the top three countries in the world in terms of cinema admissions per capita.[4] According to domestic box office data, almost twenty million people go to the movies on the average weekend, which is much more than on week days and represents a considerable fraction of the population. The age structure of moviegoers resembles that of the general population as far as the adult group is concerned, yet teens and young adults (12-24 year-olds) tend to be overrepresented and old people (60+ year-olds) tend to be underrepresented (MPAA, 2007). There is also evidence that moviegoers are better educated, have higher incomes, are more likely to use financial services (e.g. home computer banking, debit cards, Keogh plan) and entertainment technology (e.g. Internet), travel more, have a more active lifestyle, and are more involved in social activities than the average American (Arbitron, 2003); furthermore, moviegoers tend to be early adopters of new products/services and decision influencers (Arbitron, 2007). Since stock market participation is positively correlated to such factors as income and wealth (Guiso et al., 2003), education and financial literacy (Bertaut, 1998; van Rooij et al., 2007), Internet

[4] http://stats.uis.unesco.org/unesco/ReportFolders/ReportFolders.aspx.

usage (Bogan, 2008) and social interactions (Hong et al., 2004), moviegoers appear to be more likely to participate in the equity market than the average American.

(ii) Comedy movies, especially, attract large audiences in the domestic market (see Figure 2). Comedy blockbusters generate sales that tend to be concentrated in the first few weekends after release and quickly fall over time. For this reason, both the number of screens dedicated to comedies (see Figure 3) and comedy admissions exhibit a conspicuous variability over time, which makes it possible to identify the effect of interest.

(iii) There is both lab and field evidence that the movie experience can produce intense and unambiguous mood states in moviegoers, which in turn can translate into changes in risk propensity/perception; some of this evidence has been discussed in sections 2.1 and 2.2. More specifically, funny (sad) movie clips have been found to induce positive (negative) emotional states in the viewer. According to Gross and Levenson (1995), the use of movie clips is one of the most effective and popular ways to manipulate subjects' emotional states; the review conducted by Gerrards-Hesse et al. (1994) also supports such a claim, and the meta-analysis employed by Westermann et al. (1996) suggests that, among the mood induction procedures adopted in the literature, videotapes and films produce the strongest effect in inducing positive mood. In the field, Forgas and Moylan (1988) and Payne et al. (1998) have conducted interviews at the entrance of movie theaters with unwary individuals leaving film performances, documenting a clear impact of movie type (happy, sad, or aggressive) on moviegoers' moods and judgments. Forgas and Moylan (1988), in particular, find no evidence of self-selection when approaching individuals *before* they entered the movie theater, but do find evidence that happy films positively affect beliefs *after* exposure.

(iv) There is evidence that individual investors are more likely to ponder trading decisions on weekends and conduct actual trades on Mondays, whereas professional investors have a propensity to trade less on Mondays (Venezia and Shapira, 2007; Chan et al., 2004; Abraham and Ikenberry, 1994). This implies that the risky investment decisions that retail investors contemplate during the weekend (and implement on the subsequent Monday) may be affected by their weekend mood, which in turn may be influenced by their exposure to comedy movies.

(v) Skeptics may point out that movie-induced emotional changes are likely to be short-lived and dissipate within a few minutes of exposure or, at most, a few hours, so that they should only have a transient effect on decision making. This is not the case, however, according to Andrade and Ariely (2009), who discuss two mechanisms through which transient emotions may have a lasting impact on decision making: (a) inferences on past affect-based decisions, and (b) behavioral consistency. The first mechanism rests upon the idea that when individuals make an initial judgment about a certain issue, such a judgment may be stored in memory and used as a basis for further assessment when a decision is required in the near future. This implies that, if the original judgment was contaminated by an incidental emotional state, then the subsequent assessment and decision will also be influenced correspondingly. In support of this hypothesis, Simonsohn (2010) finds that students' college enrollment decisions (typically made a few months after a campus visit) are affected by the weather conditions prevailing at the time of the campus visit. Ottati and Isbell (1996) also document an analogous effect of mood on the judgments reported by their subjects a week after the mood induction procedure took place. In the context of the present investigation, one may speculate that if an individual is pondering an investment decision throughout the weekend and, additionally, if she happens to briefly contemplate such a decision during or shortly after exposure to a comedy movie in a theater, then the assessment she makes at such time may influence the decision she will make later (maybe next day, or two days later) in the comfort of her home. With regard to the second mechanism, Andrade and Ariely (2009) argue that since "past actions are often used as a starting point for decision making and people tend to behave consistently with past actions and cognitions, earlier choices - unconsciously based on a fleeting incidental emotion - can become the basis for future decisions and hence outlive" the emotion itself. They provide evidence in support of this hypothesis by putting their subjects through repeated rounds of the ultimatum and dictator game and showing that the emotional changes experienced in the early stages of the game (as a result of exposure to a video clip) affect the decisions made in later stages even if such emotional changes have already vanished. In the context of the present investigation, behavioral consistency may also have relevant implications. After watching a comedy movie in the theater, an individual is called upon making sequential decisions in many daily life situations. For example, when driving home she has to decide whether to drive slowly and safely (a signal of risk aversion) or faster and recklessly (a signal of risk-loving behavior), and such a decision is likely to be influenced by the transient emotional state generated by the movie. Once an initial choice is made, it will lead the individual to infer that her decision was based on a certain set of risk preferences (e.g. "since I chose to drive slowly, I must be risk averse") and, for behavioral consistency, she will apply the same set of preferences in subsequent decisions in the near future (e.g. investment decisions).

(vi) Researchers have also documented that international markets are not fully integrated and there exists a deep home-equity bias (e.g. Levi, 1997; Lewis, 1999), so that domestic investors and institutions are likely to exert a considerable influence on the dynamics of the U.S. stock market. All of this suggests that a mood enhancement experienced during the weekend by a large segment of less sophisticated U.S. investors as a result of attending a comedy movie may well have a domestic market impact through their ensuing trades on the following Monday.

4. Data

In my empirical analysis I employ U.S. daily stock returns taken from the Center for Research in Security Prices (CRSP). More specifically, I select the equal-weighted returns and the value-weighted returns (both including distributions) calculated for the NYSE/AMEX/NASDAQ market combination over the period December 1, 1994 through December 31, 2009. In order to also examine the most recent data in some robustness tests, I also employ the returns on the S&P500, Dow Jones Industrial, NYSE Composite, and NASDAQ Composite indices, all obtained from Datastream.[5] The sample in this case extends from December 1, 1994 through May 31, 2010. To investigate a possible differential impact of positive mood on the valuation of firms exhibiting different characteristics I make use of Fama and French (1992) 10 value-weighted portfolios constructed by industry, by size, and by book-to-market ratio. Additionally, I employ CRSP value-weighted returns calculated on beta-based and standard deviation-based deciles for the NYSE/AMEX market combination.

Domestic movie box office data and movie details are taken from a database hosted on the website *www.the-numbers.com*, which collects information from film distributors, industry organizations, the specialized press, and Exhibitor Relations Co. Inc. In my analysis I focus on weekend (Friday through Sunday) box-office revenues for two reasons. First, movie attendance is much higher on weekends than during week days, which means a larger fraction of the population may be affected by movie-induced mood shifts at such times. Second, detailed weekend box-office data are available for a reasonably long period of time (from December 9, 1994 through May 28, 2010), whereas daily data are only available for the top 10 grossing movies starting from 1997. The sample that I employ comprises 808 weekends and 7,246 unique movie titles. Over this period of time, roughly 101 movies concurrently played in theaters on the average weekend, which means the

[5]The Datastream codes for such indices are S&PCOMP, DJINDUS, NYSEALL, and NASCOMP, respectively.

average movie is shown for approximately eleven weekends before leaving the theaters. Movies are classified by *www.the-numbers.com* into twelve mutually exclusive genres: comedy, adventure, drama, action, thriller/suspense, romantic comedy, horror, documentary, musical, black comedy, western, and concert/performance. The first six genres of this list account for 92% of total domestic gross revenue between January 1995 and May 2010. Comedy movies take the lion's share with approximately 24.2% of the market share (and 18% of the movie releases) over such a period, followed by adventure films and dramas.[6] To estimate the audience size by movie genre for each weekend, first I obtain annual average ticket prices from the National Association of Theater Owners (NATO), and then I follow Einav (2007) and I compute weekly ticket prices by linearly interpolating annual prices. The number of theater admissions by movie genre in each weekend is then calculated by dividing the corresponding box-office revenues by the estimated weekly ticket price (see Figure 1 and 2, and Table I). From *www.the-numbers.com* I also extract the number of theaters any given movie is playing in at a given point in time and I use this information to construct a time series of weekend theater counts by genre.[7] As a result, throughout the period under observation, I am able to measure the number of people that went to see a comedy movie (or a thriller, etc) on weekend *t* and the number of theaters showing a comedy movie (or a thriller, etc) on weekend *t* (see Figure 3).

Following Dahl and DellaVigna (2009), I collect movie violence ratings from *www.kids-in-mind.com* and I construct a time series of weekend audiences (and theater counts) for strongly violent movies featuring a rating ≥ 8 (see Appendix). As an alternative, I also consider the movie ratings from the Motion Picture Association of America (MPAA). To create a proxy of movie "quality", which I later use to create an instrument for comedy movie attendance, I employ user evaluations from the Internet Movie Database (IMDB), a popular website that features information and message boards about movies, TV shows, actors, and the like (see Appendix).

I construct a set of controls using data from disparate sources. I create a Monday dummy (*M*) that takes value 1 on Mondays and zero otherwise (Gibbons and Hess, 1981; Ko et al., 1997), and a *Tax* dummy that takes value 1 over the first seven days of January and 0 otherwise (Keim,

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[6]For a very small number of movies in the database the genre label is missing. They account for roughly 0.12% of domestic gross revenue in the sample under observation. These are typically small movie productions that tend to attract a negligible number of moviegoers. For simplicity, in all the computations reported below I assume these movies do not belong to the comedy genre, but I do include their audiences in the count of total weekend moviegoers. As an alternative, in unreported calculations, I assume that all these movies belong to the comedy genre and I obtain virtually identical results.

[7]According to *www.the-numbers.com*'s definition, a theater is "any place a movie is showing from the smallest cinema on the art house circuit to the largest megaplex".

1983; Dyl and Maberly, 1992). The remaining environmental controls, which are partly drawn from the behavioral finance literature and are meant to capture widespread mood fluctuations across the population, are described in the Appendix.

5. Empirical Analysis

5.1. Baseline Model

I begin my empirical analysis with a simple OLS model that regresses stock returns on comedy movie attendance and a few controls. More in detail, I estimate the following equation and perform statistical inference adopting Newey-West (1987) adjusted standard errors (max 5 lags):

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \gamma_{Monday} M_t + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \varepsilon_t \qquad (1)$$

where R_t measures the CRSP equal-weighted (or value-weighted) return on day t, M_t is a dummy that takes value 1 on Mondays and 0 otherwise, $Comedy_{t-1}$ is the audience for comedy movies on the weekend (Friday through Sunday) that precedes Monday t, and Tax_t is a dummy that takes value 1 over the first seven days of January and 0 otherwise.[8] Five lagged returns are included in each regression model to control for the serial autocorrelation of equity returns (e.g. Tetlock, 2007). The results for the equal-weighted and value-weighted returns are reported in column (1) and (2), respectively, of Table III. The sign and magnitude of the coefficient on *Comedy* are consistent across the two return definitions. Other things equal, a 10% (one standard deviation) increase in comedy admissions on a given weekend is estimated to be followed by a 0.01% (0.07%) reduction in equity returns on the subsequent Monday. When CRSP equal-weighted (value-weighted) returns are considered, the marginal effect is statistically significant at the 5% (10%) level. The sign of this effect is consistent with a fall in investors' net demand for risky assets, which in turn is consistent with domestic investors behaving more cautiously when experiencing a movie-induced positive mood.

My next step is to add to the regression equation a control for the overall weekend movie attendance (i.e. regardless of movie genre). There are several reasons for doing so. First, movie ticket sales obviously affect film production companies' revenues (and expected revenues on the

[8] More precisely, the variable *Comedy* measures the audience for comedy movies + 1 person. This measurement technique is applied throughout the paper to all variables that measure some type of movie attendance and enter the regression model in a logarithmic form, so that they never take value 0.

future sale of DVD's, gadgets, etc), which means that an increase (decrease) in movie admissions may have a direct economic effect on the value of the listed companies that own the corresponding film studios, in turn influencing stock returns.[9] By controlling for the total ticket sales, the econometrician can attempt to hold constant such economic effects. Second, since movie release dates and consumer demand for movies seem to be subject to some seasonal dynamics (Einav, 2007), and there is also evidence that the stock market exhibits some seasonal behaviors (e.g. Kamstra et al., 2003), adding to the model a covariate that measures overall movie attendance should control for seasonalities that are common to all movie genres. Third, the experience of going to the movies, *per se* (i.e. regardless of movie genre), may have some influence on people's emotional states. Leisure activities, among which moviegoing, can provide relaxation and recovery from fatigue, reduce anxiety (Hull and Michael, 1995), reduce family conflict, help individuals "to overcome loneliness, and to deal with stress and tensions" (Kraus, 1998), allow a little escapism and excitement, and "liberate people from the drudgery associated with their daily routine of thought and action" (Patterson, 2006). Uhrig (2005) finds some evidence that cinema attendance may reduce anxiety and depression, and boost life satisfaction. Johnson (2000) even claims that watching movies may have a therapeutic effect, as it stimulates empathy and allows viewers to "have experiences that can help us see ourselves and our problems more clearly". Furthermore, the audio-visual stimulation generated by the cinematic experience may produce an increased physiological arousal in the viewer (Reeves et al., 1985; Lang, 1990; Carpentier and Potter, 2007), which has been linked to higher risk seeking (Mano, 1994). It is important to notice that, in the lab, treatment and control groups are forced to watch either a happy or a neutral (or sad) movie clip, so that all subjects are exposed to the same cinematic experience (except for the movie type). In their natural environment, instead, individuals optimally choose between going to the movies and their other preferred interest (e.g. staying at home, shopping, working, etc). As a result, in the field, the impact of a happy movie on the demand for risky assets is the sum of a direct and an indirect effect. The direct effect, which is the one captured in the lab, results from the impact that a movie-induced positive mood has on risk propensity. The AIM and MMH make two opposite predictions on the sign of this impact. The indirect effect, instead, results from the fact that going to the movies displaces the consumer's next-best alternative activity, which might also have affected her

[9] Between 1995 and 2009, approximately 93% of the gross box-office revenues were generated by film studios that are currently owned by one of the following companies: Walt Disney Company, Time Warner, Sony Corporation, Viacom, News Corporation, General Electric Company, and Lions Gate Entertainment Corporation. These companies are presently listed on either the NYSE or NASDAQ.

emotional state. By controlling for the total number of people that go to the movies on a given weekend, one may hope to control for this indirect effect (assuming that the foregone activity is independent of the movie genre chosen by the consumer). The regression equation thus becomes:

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t + \\ + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \varepsilon_t \tag{2}$$

where $Moviegoers_{t-1}$ measures total movie admissions (i.e. regardless of movie genre) on the weekend that precedes Monday t. The results are reported in column (3) and (4) of Table III. The estimated coefficient on *Comedy* is virtually unaffected by this inclusion. Also, there seems to be no evidence that going to the movies per se has any impact on aggregate equity returns relative to the foregone alternative activity, as the coefficient on *Moviegoers* is estimated to be close to zero and is statistically insignificant across the two return definitions.

One may worry that comedy admissions and overall movie admissions do not share the same seasonal cycle, so that the variable *Moviegoers* does not accurately control for the peculiar seasonal pattern of comedy admissions. My next step is therefore to add a further set of seasonal controls to the model, which becomes:

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t + \\ + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \sum_{k=1}^{11} \gamma_{2k} Month_{kt} + \varepsilon_t \tag{3}$$

where $Month_{kt}$ is a monthly dummy that takes value 1 in the k^{th} calendar month, and 0 otherwise. Model [3]'s estimated coefficients are collected in Table IV and do not reveal any relevant deviation from the outcomes of model [2], which suggests that the correlation between comedy attendance and stock returns cannot be explained by broad seasonal patterns.

5.2. Endogeneity Issues

5.2.1. Controlling for Environmental Mood Triggers

Even if seasonality is ruled out, the correlation between comedy movie attendance and stock returns may still be the result of some unobserved factors that jointly affect the size of comedy audiences on weekends and equity returns on the following Mondays. People's pre-existing moods over the weekend may have an impact on their choice between going to the movies and alternative forms of leisure, their choice between alternative movie genres, and their investment decisions that will be implemented on the subsequent Monday. According to the *mood-management theory* (MMT) (Zillmann, 1998), entertainment choices can be at least partially explained based on the assumption that "individuals have both a need and a desire to maintain positive mood states and terminate negative ones" (Strizhakova and Krcmar, 2007). Within this framework, an incidental sad emotional state is believed to lead people to gravitate around mood-lifting media choices, such as watching a comedy movie. Consequently, an increase in comedy movie attendance on a given weekend may be the result of a previous widespread rise in negative mood across the population, which may also be the driving force behind the (negative) reaction of the stock market on the following Monday. This would generate a downward bias in the correlation between comedy movie attendance and equity returns. However, this is not the only possibility; indeed, the existence of a market for sad films represents a paradox that the MMT cannot explain (Oliver, 2003). In fact, some authors argue that a sad emotional state may actually lead individuals toward choosing mood-congruent media content, as comparing oneself to other people who are suffering even more might cause a mood enhancement and a boost of self-esteem in the viewer (Oliver, 1993; Oliver et al. 1998). If people are likely to wallow in their moods, as this interpretation suggests, then an incidental sad emotional state would be expected to encourage them to refrain from watching funny movies. Such an unobserved factor would lead to an upward bias in the correlation between comedy movie attendance and stock returns.

To address these endogeneity issues I employ two strategies. In this section I attempt to control for some physical factors that may generate collective mood shifts across the population over the weekend, and in the next one I adopt an instrumental variables approach. More specifically, here I augment model [3] with a set of environmental covariates, as follows:

$$\begin{aligned} R_t = {} & \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t + \\ & + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \sum_{k=1}^{11} \gamma_{2k} Month_{kt} + \mathrm{X}_t^{'} \delta + \varepsilon_t \end{aligned} \tag{4}$$

where X_t is a vector of daily variables proxying for the seasonal affective disorder in the U.S., disturbances of the Earth's magnetosphere, the lunar cycle, and the percentage of Americans that on day *t-1* and *t-2* have been exposed to extremely high temperatures, extremely low temperatures, strong winds, snow, rain, fog, hail, thunderstorms, and tornados (see Appendix and Table II). X_t

also contains three variables that measure the average temperature, rainfall (yes=1, no=0), and wind speed in New York City. A relevant subset of model [4]'s estimated coefficients is reported in Table V, revealing no substantial changes in the marginal effect of *Comedy* compared to Table IV. The same applies to the coefficient on *Moviegoers*, which is again estimated to be close to zero and statistically insignificant. Among the environmental triggers considered here, only the coefficients on the *snow* (at lag 1) and *thunder* (at lag 2) proxies appear to be marginally statistically significant. For this reason, this set of controls will be excluded throughout the rest of the analysis. It is worth emphasizing, though, that all the results presented below are virtually unaffected when this set of controls is included.

5.2.2. Instrumental Variables Estimation

The second approach consists in instrumenting for weekend comedy movie audience using information on the same weekend's percentage of theaters in which comedies are playing. According to Moretti (2008), "the number of screens dedicated to a movie in its opening weekend reflects the sales expectations held by the market", as theater owners obviously have an incentive to maximize profits by correctly predicting consumer demand. This suggests that the number of theater screens allocated to a given movie should be highly correlated to the number of admissions to the same movie. Furthermore, the former seems to represent a reasonable source of exogenous variation in the latter; for instance, if few theaters are covering a given movie genre at a given point in time, then consumers may be "forced" to either choose an alternative genre or an alternative form of leisure.[10] Additionally, since screen allocations are finalized one to two weeks in advance by theater owners (Moretti, 2008; Dahl and DellaVigna, 2009), the percentage of theaters in which comedies are playing on weekend *t* is essentially unrelated to (a) unexpected economic news, (b) pre-existing mood conditions, and (c) other events that may take place during weekend *t* and will be incorporated into stock prices on the following Monday. In the end, this IV strategy should remove the effects of any short-term shocks that modify comedy movie attendance on a given weekend and equity returns on the subsequent Monday but are not present one or two weeks before.

Estimating equation [3] by 2SLS generates the results reported in column (1) of Table VI (equal-weighted returns) and Table VII (value-weighted returns). I compute *HAC* robust standard

[10] As Figure 3 shows, at times even less than 5% of the theaters are dedicated to comedy movies, whereas at some other times this value increases to 50%.

errors following Baum et al. (2007).[11] Based on the C statistic test (Baum et al., 2010), the null hypothesis that comedy movie attendance can be treated as exogenous is rejected at the 10% confidence level. To document the strength of the instrument used here, I report the Wald rk F statistic based on Kleibergen and Paap (2006). According to Baum et al. (2007), when testing for weak identification in the presence of non i.i.d. errors, it may be a good idea to "refer to the older «rule of thumb» of Staiger and Stock (1997) that the F-statistic should be at least 10 for weak identification not to be considered a problem". The K-P statistics in Table VI and VII are 256 and 258, respectively, and the coefficient on the instrument is highly significant in the first stage regression (not reported here), which suggests that the estimates are unlikely to suffer from the weak instrument problem.

Instrumenting makes the correlation between comedy attendance and stock returns become more negative. According to the IV regression, other things equal, a 10% (one standard deviation) rise in comedy movie admissions on a given weekend is estimated to be followed by roughly a 0.02% (0.13%) fall in U.S. stock returns on the following Monday. This marginal effect is statistically significant at the 5% level, and it also appears to be economically relevant given the substantial variability to which comedy audiences are subject (Figure 2). Conversely, the coefficient on *Moviegoers* is not statistically distinguishable from zero.

The line of reasoning followed in the previous section suggests that the total number of weekend moviegoers may also be endogenous (e.g. Pham, 1998), so my next step is to also instrument for overall movie attendance on a given weekend using information on the following weekend's overall movie audience. This strategy takes advantage of the regularities in the weekly decrease in movie admissions, which is a well known reality in the movie industry (e.g. Moretti, 2008), and should purge the estimates of any short-term shocks that may affect both overall weekend movie admissions and Monday's equity returns. The results are reported in column (2) and reveal that the estimated coefficient on *Comedy* is not appreciably influenced by whether *Moviegoers* is instrumented for or not. What is different, however, is that the coefficient on *Moviegoers* is now positive and statistically significant at the 10% level. More in detail, when both variables are instrumented for, a 10% (one standard deviation) increase in overall movie admissions on a given weekend is estimated to be followed by a 0.06% (0.15%) increase in stock returns, provided there is no change in the audience of comedy movies. If, instead, all the additional

[11] The *IVREG2* Stata routine that I run uses the Bartlett kernel function and an automatic bandwidth selection criterion following Newey and West (1994).

moviegoers decide to attend a comedy, then the overall impact on the following stock market performance is estimated to be slightly negative (-0.02%), as the marginal effect of *Comedy* dominates over the marginal effect of *Moviegoers*.[12] Another way to interpret the results is that, holding constant the total number of people that go to the movies on a given weekend, an increase in the number of individuals who are exposed to a comedy is followed by a decrease in equity returns. This suggests that while increased moviegoing, in general, can have a positive impact on the demand for risky assets (relative to the foregone activity), exposure to happy movies, in particular, is estimated to have a negative impact on such a demand.

As far as the effect of overall movie attendance is concerned, this appears unlikely to be the sole result of direct economic benefits. A 10% increase in movie admissions, evaluated at the mean value of *Moviegoers*, is equivalent to roughly 1.9 million additional tickets sold. Even assuming that each moviegoer later purchases (rents) a corresponding DVD and movie related merchandise, an amount of $100 million (at 2010 prices) can be considered as a rough upper bound on the total economic revenues involved. Conversely, taking into account the combined average market capitalization of NYSE, NASDAQ, and AMEX between 1994 and 2009 (over $13.4 trillion), a 0.06% increase in stock returns is roughly equivalent to an $8 billion market value gain. As such, it seems the case that the behavioral effects described in section 5.1 also play a major role. I will provide additional evidence on this when analyzing the performance of different portfolios of stocks sorted by industry in section 5.5.

5.3. Controlling for Movie Violence and Frightening Thrills

Previous research has shown that exposure to violent media, including motion pictures featuring violent material, can elicit transient aggressive behaviors in the viewer (e.g. Anderson, 1997; Huesmann and Taylor, 2006; Dahl and DellaVigna, 2009), and the latter have been found to be positively related to risk-taking propensity (e.g. Caspi et al., 1997; Krcmar and Greene, 2000; Zuckerman and Kuhlman, 2000; Fessler et al., 2004; Cao and Wei, 2005). Researchers have also documented that frightening entertainment (e.g. thriller or horror movies) can cause long-lasting

[12] A 10% increase in overall movie admissions is equivalent to 1.9 million additional viewers when *Moviegoers* is evaluated at its mean value. If all the extra viewers go to watch a comedy movie, this implies a 40% increase in comedy attendance compared to its mean value. The 10% increase in *Moviegoers* is estimated to increase stock returns by 0.06% while the 40% increase in *Comedy* is estimated to reduce stock returns by 0.08%, so that the combined effect is a decrease of approximately 0.02%.

fear and anxiety in the viewers (Harrison and Cantor, 1999; Cantor, 2004; Cantor, 2006), and such emotional reactions may promote pessimistic risk estimates and risk avoidance (Raghunathan and Pham, 1999; Lerner and Keltner, 2001; Maner and Schmidt, 2006; Kaplanski and Levy, 2009). In order to control for the effect that violent and thrill-inducing movie content may have on viewers' emotional states and risk attitudes, I add to model [3] two covariates, as follows:

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t + \\ + \beta_{Violent} M_t \times \ln(Violent_{t-1}) + \beta_{Thriller} M_t \times \ln(Thriller_{t-1}) + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \\ + \sum_{k=1}^{11} \gamma_{2k} Month_{kt} + \varepsilon_t \tag{5}$$

where $Violent_{t\text{-}1}$ is the audience for strongly violent movies on the weekend that precedes Monday t, and $Thriller_{t\text{-}1}$ measures the weekend audience for movies classified in the thriller/suspense genre.[13] As in Dahl and DellaVigna (2009), here I define a movie as strongly violent if it has received a violence rating ≥ 8 by *www.kids-in-mind.com* (see Appendix).

The results of the 2SLS regression (where I instrument for *Comedy* and *Moviegoers* as detailed in the previous section) are reported in column (3) of Table VI (equal-weighted returns) and Table VII (value-weighted returns). Though the coefficients on the two additional covariates exhibit the expected sign (positive for *Violent* and negative for *Thriller*), the estimates do not provide enough statistical evidence that they have any explanatory power and, more importantly, the coefficients on *Comedy* and *Moviegoers* are not altered in a significant way compared to columns (1) and (2). When I also instrument for *Violent* and *Thriller* (using as instruments the percentage of theaters dedicated to strongly violent movies and to thriller/suspense movies, respectively), in the case of the equal-weighted returns I indeed find some evidence (see column (4)) consistent with the view that exposure to violent media leads to risk-prone behavior. More in detail, a 10% (one standard deviation) increase in violent movie admissions on a given weekend is estimated to be followed by roughly a 0.7 (3.5) basis-point increase in stock returns on the subsequent Monday. This effect is statistically significant at the 10% level; even if it does not seem to be particularly relevant from an economic perspective, it represents an important piece of evidence as it is consistent with the general story presented here, according to which exposure to

[13] Here I do not combine the audiences for thriller/suspense and horror movies since there is evidence that the latter tend to disproportionally attract teenagers (Simonoff and Sparrow, 2000; Rockoff, 2002), who are unlikely to play any relevant role in the stock market. Unreported calculations reveal that such a choice has no influence on the findings reported below.

certain types of movie content may affect decisions under risk. Column (4) also reveals that the coefficient on *Comedy* is still statistically significant and has not experienced any relevant change in magnitude compared to columns (1) and (2). Last, though instrumenting for *Thriller* makes its coefficient slightly more negative, it has no impact on its statistical insignificance.

In unreported computations I use the rating system employed by the MPAA in place of the system used by *www.kids-in-mind.com*. In this case I define a movie as strongly violent if it has received a rating of either R (Restricted) or NC-17 (No one 17 and under admitted). Again, the coefficient on *Violent* is estimated to be positive, yet the results do not yield enough statistical evidence of a significant correlation between violent movie admissions and stock returns. This may follow from a lack of a true link between the two variables, or it might also result from the fact that the MPAA rating system is less detailed and is based on a combined appraisal of the amount of violence, sex, and profanity featured by a given movie. Anyhow, using the MPAA ratings does not affect in any way the statistical evidence on the marginal effect of *Comedy*.

5.4. Robustness Tests

5.4.1. Alternative Instruments

The benchmark instrument for weekend comedy attendance employed in the previous sections uses information on the percentage of theaters in which a comedy movie is playing on that weekend. Here I re-estimate model [3] using some alternative instruments to test how sensitive the results are to this initial choice.

First, I employ as an alternative instrument the *number* of theaters dedicated to comedy movies on a given weekend. The estimates, computed using the same instrument for *Moviegoers* as in the preceding sections, are reported in column (1) of Table VIII (equal-weighted returns) and Table IX (value-weighted returns). The coefficient on *Comedy* is now slightly more negative than with the benchmark instrument, and it is still statistically significant at the 5% level.

Second, I employ an alternative instrument that uses information on the average "quality" of the comedy movies playing on a given weekend. To proxy for the quality of a comedy movie I employ a measure based on IMDB U.S. users' ratings; more specifically, for each comedy movie in the sample I collect the average rating posted by U.S. users of the IMDB.[14] Then, for each weekend

[14] The analysis produces very similar results when I employ the ratings provided by either all IMDB users (i.e. regardless of nationality) or all IMDB users above 18.

in the sample I construct the simple average of the average ratings obtained by the comedy movies that are playing in that weekend. My conjecture here is that there exists a correlation between the overall quality of the pool of comedies that are playing on a given weekend and the number of admissions to such movies. However, in practice the former variable does not seem to predict very well the latter. Hence, I supplement it with information on the number of theaters in which a comedy is playing. The results are reported in column (2) and, once again, they provide some evidence in support of the mood effect discussed here. Based on the Hansen J statistic reported at the bottom of the column, one fails to reject the null hypothesis that these instruments are valid instruments at conventional significance levels. Also, the coefficient on *Comedy* is negative, statistically significant, and similar in magnitude to what has been shown in the previous sections.

Third, I instrument for comedy movie attendance on a given weekend using information on the average quality of the comedies that are playing on that same weekend, the number of theaters in which a comedy is playing on the following weekend, and the number of theaters in which a comedy is playing on the weekend after the following weekend. This strategy exploits both the persistence in screen allocations over time and the correlation that exists between the alleged quality of a movie and the size of the audience it is able to attract. The estimates are collected in column (3). In the case of the equal-weighted returns the coefficient on *Comedy* is negative and significant at the 10% level. A negative and marginally significant coefficient (p-value = 0.11) is also obtained when value-weighted returns are considered. In both cases the marginal effect is estimated to be somewhat less strong than with the previous instruments. Here a 10% (one standard deviation) increase in comedy movie admissions is estimated to reduce stock returns by approximately 1.8 (11) basis points, *ceteris paribus*. Fourth, I combine all the alternative instruments presented in this section. The results are reported in column (4) and tell once again a consistent story. The coefficient on *Comedy* is estimated to be negative and statistically significant at the 5% level.

Last, in unreported computations, I augment the benchmark instrument with two instruments that measure (1) the percentage of movie titles playing on a given weekend that are comedies and (2) the average "quality" of the comedy movies playing on the same weekend, as proxied by IMDB users' ratings. The results that I obtain are slightly stronger than with the benchmark instrument and are similar to the ones reported in Table VIII and Table IX. To summarize, it seems the case that the findings presented earlier are robust to the use of different sets of instruments.

5.4.2. Market Liquidity, Holiday Controls, and TV Audience controls

In principle, when investors are out on the weekend having a great time watching a comedy movie with friends/families, they may have less time to catch up with the economic news, and think about their portfolios and potential trading decisions. If, as a result, they feel uninformed and unready to trade, they may decide to simply stay away from the market on the following Monday, thus causing a reduced order flow. A fall in liquidity may then persuade sellers to accept a lower price, which might be responsible for the effect documented here.

Tetlock (2007) captures liquidity effects using trading volume and controls for the influence of other possible market frictions using lagged return volatility. Here, to examine the liquidity and frictions hypothesis, I follow a similar approach and I construct a measure of past volatility of stock returns and a detrended trading volume series. More specifically, I employ a time series of daily trading volume on the NYSE, which I detrend after a logarithmic transformation of the data.[15] I also use the detrended squared residuals of the CRSP returns as a proxy for past volatility.[16] I then re-estimate model [3] adding up to five lags of these two controls and using the benchmark instrument for *Comedy*. The results are shown in column (1) of Table X (equal-weighted returns) and Table XI (value-weighted returns) for the case when *Moviegers* is not instrumented for; column (3) of the same tables, instead, reports the results for the case when I also instrument for *Moviegoers* using the instrument described in the previous sections. The estimates suggest that the mood effect documented in this study is not driven by a drop in market liquidity (at least when liquidity is proxied by trading volume) or by other market frictions (as measured here): the marginal effect of *Comedy* is still estimated to be negative and statistically significant.

One may worry that the seasonal controls included in model [3] do not completely remove the seasonal patterns that may affect both comedy movie attendance and stock returns. For instance, holidays typically increase movie attendance (Einav, 2007), and there is also evidence of abnormal stock market behaviors around their occurrence (Ariel, 1990; Kim and Park, 2009). In principle, holidays might have a distinctive effect on comedy admissions that is not already captured by the dynamics of overall movie attendance or by the monthly dummies. I therefore add to model [3]

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[15]Trading volume data are taken from Datastream (code: TVNYORK(VO)). As in Campbell, Grossman and Wang (1993) and Tetlock (2007), I detrend the data by subtracting the 60-day moving average of log daily volumes from the current log volume. All the results reported in the paper stay virtually unchanged when using the 30-day or 90-day moving average.

[16]As in Tetlock (2007), first I demean the stock returns series to obtain a residual, then I square this residual and I subtract the 60-day moving average of past squared residuals. The results reported below are robust to the use of a 30-day or 90-day moving average.

separate dummy indicators that take value 1 on the Mondays following New Year's Day, Independence Day, Veteran's day, Thanksgiving Day, Christmas Day, and Easter Day. Furthermore, I include some controls for days with high TV viewership: (1) an indicator for the Mondays following the Superbowl (see Dahl and DellaVigna, 2009), and (2) a dummy that takes value 1 on day $t+1$ if on day t a TV show finale has been broadcasted that has attracted at least 10 million viewers.[17] The results are shown in column (2) (*Moviegoers* not instrumented for) and in column (4) (*Moviegoers* instrumented for). What emerges is that the inclusion of all these covariates does not alter the sign, magnitude, and statistical significance of the coefficient on *Comedy*.

5.4.3. Business Cycle Shocks, Alternative Movie Genre Classifications, and Sensitivity to Outliers

The IV technique employed in section 5.2.2 should help clean out short-term shocks that may influence both movie attendance and stock returns. However, some long-term shocks may still have an impact on the estimates. It might be the case that during bad economic times (i.e. recessions) people try to seek refuge from reality and restore their good moods by watching funny movies more often (Schuker, 2008). In order to control for business cycle fluctuations that may boost comedy admissions and depress stock returns, I add to model [3] a set of monthly macroeconomic variables; in the spirit of Baker and Wurgler (2006), these are: growth in the industrial production index, growth in consumer durables and nondurables, growth in the consumer sentiment index, the change in the civilian unemployment rate, and a dummy variable for NBER recessions.[18] The results (not reported here) show that only the variable measuring growth in consumer sentiment turns out to be significantly (positively) related to stock returns, and the coefficients on *Comedy* and *Moviegoers* are virtually unaffected by this inclusion.

So far, in my analysis I have defined a movie as a comedy if it has been classified in the "comedy" genre by *www.the-numbers.com*, which, it is worth emphasizing, employs mutually exclusive genre labels. It is natural to wonder whether the findings are sensitive to alternative movie categorizations. In order to explore this issue I construct some alternative definitions of a comedy

[17] The data are taken from a ranking of the most watched TV series finales compiled by *http://classic-tv.com/*, a web site that features information on TV shows from the 1950's to the present. In the sample there are 46 observations featuring a TV audience in excess of 10 million people. Similar results are obtained when using alternative TV audience thresholds.

[18] The data are taken from the Federal Reserve Bank of St. Louis. The data codes are INDPRO, IPDCONGD, IPNCONGD, UMCSENT, and UNRATE, respectively.

movie. First, I consider a movie as a comedy if it has been identified by *www.the-numbers.com* as either a “comedy” or a “romantic comedy”. In a second exercise, I consider a movie as a comedy if it has been given either the label “comedy” or “black comedy”.[19] In a third exercise, I combine the three above-mentioned labels and I define a movie as a comedy if it has been assigned anyone of the following genre labels: “comedy”, “romantic comedy”, “black comedy”. I then re-estimate model [3] using the benchmark instrument for *Comedy* (and adjusting the instrument based on the new relevant definition of a comedy movie). I run the 2SLS regression both instrumenting for *Moviegoers* and without doing so. The results, not reported here due to space limitations, suggest that, under all these three alternative definitions of a comedy movie, the coefficient on *Comedy* is estimated to be negative and statistically significant at the 5% level. Actually, using anyone of these three alternative definitions renders the marginal effect of *Comedy* slighly more negative than in the benchmark case, which suggests the original definition may be considered as a conservative measure. More specifically, when employing the most general definition of a comedy movie that embraces all three genre labels (“comedy”, “romantic comedy”, and “black comedy”), I estimate than a 10% (one standard deviation) increase in comedy movie attendance on a given weekend lowers U.S. stock returns by 3 (15) basis points on the following Monday.

In order to verify whether the findings presented above are sensitive to outliers, I also re-estimate model [3] using the benchmark instrument and including a dummy indicator for the 1% of observations with the largest comedy movie attendance. I repeat the same exercise using a 2% and 3% cut-off rule, respectively, and also including a dummy indicator for the 1% (2%, 3%) of observations with the smallest number of comedy admissions. The sign, size, and statistical significance of the estimated coefficient on *Comedy* turn out to be qualitatively unaffected by this addition.

Last, to test whether the results are robust to alternative measures of aggregate stock returns, I employ the returns on some broad indices of the U.S. stock market in place of the CRSP returns. This strategy also brings about an extension of the data sample up to May 31, 2010, whereas the original sample stops at the end of December 2010. More in detail, I compute equity returns using the S&P500, the Dow Jones Industrial, the NYSE Composite, and the Nasdaq Composite index, respectively. I then re-estimate model [3] using the benchmark instrument for

[19] The average audience size for movies belonging to the ”romantic comedy” or ”black comedy” genres is much smaller than for movies falling into the ”comedy” genre. More in detail, in the sample 1.16 million people watch a ”romantic comedy” and 0.85 million people watch a ”black comedy” on the average weekend. As shown in Table I, the average weekend audience for movies belonging to the “comedy” genre is approximately 4.67 million people.

Comedy (both instrumenting for *Moviegoers* and without doing so). What emerges from the estimates (not reported here) is that, independently of the market index adopted, the marginal effect of *Comedy* is estimated to be negative and statistically significant at conventional levels. The point estimate of this coefficient takes the most negative value in the case of the Nasdaq index, for which I find that a 10% (one standard deviation) rise in comedy admissions reduces stock returns by 3.7 (22) basis points. Using the returns on the Dow index, instead, gives rise to the least negative point estimate, according to which the reduction in equity returns would be approximately 1.7 (10) basis points.

5.5. Impact on the Cross-Section of Stock Returns

The last portion of my analysis is devoted to shedding more light on the link of causality by examining the cross section of stock returns. Investor sentiment appears to exert a larger influence on the pricing of stocks whose intrinsic values are highly subjective and that are more difficult to arbitrage (Baker and Wurgler, 2006; Kumar, 2009). Baker and Wurgler (2006) find evidence that behavioral biases are stronger for (among others) high-volatility stocks. I therefore re-estimate model [3] using as a dependent variable the CRSP returns calculated on standard deviation-based deciles and employing the benchmark instruments for *Comedy* and *Moviegoers*. The results, reported in Table XII and depicted in Figure 4 (panel c), reveal a nearly monotonic volatility effect. The first decile (highest standard deviations) exhibits the largest marginal effect of *Comedy* (significant at the 1% level) and the magnitude of this effect tends to decrease (in absolute value) as more volatile deciles are considered. In the case of the least volatile decile, though the size of the coefficient is still negative, the effect is no longer statistically significant at conventional levels.

Kumar (2009) documents that investor sentiment has a stronger impact on stocks featuring high cash flow volatility and earnings volatility, the rationale being that these two factors increase valuation uncertainty. Here I use a firm's equity beta to proxy for these two variables, and I also employ a classification of firms by industry, assuming that stocks belonging to less stable industries (e.g. *HiTech*) suffer from more valuation uncertainty than stocks belonging to stable ones (e.g. *Nodur* and *Utils*). This choice is based on the evidence that beta is positively correlated to earnings volatility (Bildersee, 1975; Minton and Schrand, 1999) and cash flow volatility (Ismail and Kim, 1989; Hunt et al. 1997). Moreover, according to Coles and Loewenstein (1988) and Coles et al.

(1995), stocks characterized by high estimation uncertainty tend to have high equilibrium betas. I therefore re-estimate model [3] using as a dependent variable the CRSP returns calculated on beta-based deciles and also using Fama and French (1992) 10 value-weighted portfolios constructed by industry. The analysis of the beta-based deciles reveals a roughly monotonic relationship between the size of the mood effect and companies' betas (see Table XIII and Figure 4 (panel b)). In the case of stocks in the first decile (highest betas), a 10% (one standard deviation) increase in comedy admissions is estimated to reduce equity returns by 4.6 (27) basis points. On the other hand, the coefficient on *Comedy* is close to zero and statistically insignificant when the tenth decile is scrutinized. The examination of the industry-based portfolios also seems to generate results that are consistent with the behavioral story presented here (see Table XIV). As Figure 4 (panel a) reveals, the most volatile industries (*HiTech*, *Other*, *Durbl*, and *Telcm*) tend to cluster on one side of the industry spectrum (featuring the strongest effects), while the most stable ones (*Nodur*, *Utils*, *Enrgy*, and *Hlth*) tend to cluster on the opposite side (smallest effects).[20] Furthermore, the coefficient on *Comedy* is statistically insignificant when the least volatile industries are considered. The analysis by industry also sheds light on the interpretation of the coefficient on *Moviegoers*. Such a coefficient is positive and statistically significant not only in the case of the *Other* portfolio (which includes companies in the entertainment industry, and therefore many of the companies by which film studios are owned), but also for the cases of the *Manuf*, *Shops*, and *Utils* portfolios. This further suggests that this variable is not simply picking up the direct economic effects of movie ticket sales (and expected revenues from DVD's and merchandising), but it is also measuring some behavioral effects that are likely to originate from the cinematic experience per se (relative to the foregone alternative activity).

Baker and Wurgler (2006) also find support for the view that smaller stocks, extreme-growth stocks, and distressed stocks are more likely to be subject to behavioral biases. Based on this insight, here I examine the behavior of the returns on Fama and French (1992) 10 portfolios sorted by size and book-to-market ratio. Table XV and Figure 4 (panel e) do not reveal any relevant pattern with respect to the size variable, yet there is evidence of a statistically significant mood effect across all size deciles. Baker and Wurgler (2006) suggest that exceedingly high book-to-market ratios may signal distressed stocks, whereas exceedingly low book-to-market ratios may signal extreme-growth stocks. This interpretation would imply an inverted U-shape pattern in the

[20] The *Other* portfolio contains firms from the following industries: building materials, business services, construction, entertainment, finance, hotels, mines, and transportation.

magnitude of the mood effect analyzed here (i.e. strongest effects at the two ends of the book-to-market range). Though Table XVI and Figure 4 (panel d) show that, indeed, the coefficient on *Comedy* seems to be larger (in absolute value) at the two extremes of the spectrum, the differences are relatively small and statistically insignificant. As such, there seems to be not enough statistical evidence of a differential mood effect based on size and book-to-market ratio.

6. Concluding remarks

In this study, by exploiting the natural experiment provided by the time-series variation in the theatrical release of comedy movies, I find that a rise in comedy admissions on a given weekend is followed by a fall in stock returns on the subsequent Monday. Conversely, an increase in overall movie attendance (i.e. regardless of movie genre) is estimated to be followed by an increase in equity returns, possibly as a result of the direct economic effects of ticket sales and the psychological benefits (e.g. reduced anxiety) that the cinematic experience per se may provide relative to the foregone alternative activity. To explain this discrepancy I draw upon the experimental psychology literature, which shows that exposure to happy movie clips (e.g. comedies) can trigger positive mood, which in turn may induce people to behave more cautiously and avoid risk, especially when the stakes are high and large losses are possible, in order to preserve their good emotional states. Therefore, the main hypothesis that I propose in this study is that the wave of positive mood that stems from a wider exposure to comedy movies causes a decrease in risk-taking propensity across the population and a short-term drop in the demand for risky assets, thus adversely affecting equilibrium prices in the stock market. While it is possible that the negative reaction of the market may result from a more intense *perception* of risk after exposure, this interpretation is not supported by the available experimental evidence, according to which happy moods tend to lead people to overestimate (underestimate) the likelihood of positive (negative) future outcomes.

Compared to the existing field studies on the relationship between mood and investment in risky assets, this field investigation appears to be more deeply rooted into the available experimental evidence, as it focuses directly on a mood-shifting mechanism (i.e. exposure to movie clips) that is widely employed in the laboratory, thus allowing a more direct comparison of the results. It should be highlighted that the evidence that I present contradicts the findings of (among others) Saunders (1993), Hirshleifer and Shumway (2003), and Ashton et al. (2003). These authors argue that, in the field, positive mood (supposedly triggered by sunshine or wins in international soccer games, respectively) has a positive impact on stock returns. The data that I analyze seem to tell the opposite story. It might be the case that not all happy moods are alike, and the source of the mood state plays a relevant role that should be taken into account. Future research should investigate this issue and also make sure that the approaches employed in the field are replicated in the lab (and viceversa). With regard to the specific findings of this study, two aspects may deserve further scientific scrutiny. First, future experimental studies may want to shed more light on the precise mechanisms through which exposure to the cinematic experience *per se* seems to foster the demand for risky assets. Second, it may be interesting to determine whether it is possible to obtain abnormal returns by implementing a trading strategy based on the regularities discussed here.

Appendix

A. Movie Violence Ratings

Following Dahl and DellaVigna (2009), I collect movie violence ratings from *www.kids-in-mind.com*. Such a website is run by a non-profit organization that, through the work of trained volunteers, assigns a violence rating to feature films on a 0-to-10 point scale (10 defining the most violent content). As in Dahl and DellaVigna (2009), I classify movies into three categories: strongly violent (rating ≥ 8), mildly violent (5 ≤ rating < 8), and non-violent (rating < 5).[21] As the authors note, "violent movies are disproportionally more likely to be in the action/adventure and horror genres and are very unlikely to be in the comedy genre". I then match these ratings to the box-office revenue data from *www.the-numbers.com* to construct a time series of weekend audiences for strongly violent movies. In a similar way, I also construct a time series of theater counts for strongly violent movies. As an alternative, I also consider the movie ratings from the Motion Picture Association of America (MPAA). MPAA's ratings fall into one of five categories (G, PG, PG-13, R, and NC-17) and are based on a combined assessment of content factors such as sex, violence, nudity, language, and drug use. As such, the MPAA's rating system provides a coarser measure of movie violence than *kids-in-mind*'s system. To construct a measure of weekend audience and theater counts for violent movies based on MPAA's ratings I take the ratings R (Restricted) and NC-17 (No one 17 and under admitted) as proxies for violent content and then I match these ratings to the box-office revenue data from *www.the-numbers.com*.[22]

B. Movie Quality Proxies

Not all movies are equally enjoyable and perhaps not all of them achieve the goal of attracting and entertaining large audiences. To construct a proxy of movie "quality", which I use to create an instrument for comedy movie attendance, I employ user evaluations from the Internet Movie Database (IMDB). The IMDB also allows users to rate movies based on a scale from 1 (awful) to 10 (excellent) and publishes weighted average ratings after applying various

[21]For a small number of movies the violence rating is missing. Since the declared purpose of this non-profit organization is to protect kids from exposure to violent content, it seems likely that the missing violence ratings mainly involve non-violent movies and/or movies with small audiences. As such, I believe that the data I employ represent a pretty accurate measure of the number of people exposed to strongly violent movies in a given weekend.

[22]In the sample, the number of movies in the NC-17 category is negligible. Considering the R category only does not alter the results presented below. For a small number of movies in the sample the MPAA rating is missing. Overall, they represent approximately 1% of the revenue market share between 1995 and 2010. To address this issue I follow the same approach described in footnote 6.

(undisclosed) filters to the raw data "in order to eliminate and reduce attempts at «vote stuffing»". The IMDB also provides some demographic breakdowns of the voting patterns, which I exploit to create a quality rating for each comedy movie in the sample according to three categories of voters: IMDB users, IMDB users above 18, and IMDB U.S. users. The number of votes underlying these ratings is relatively high; speaking of the first (third) category, 73.1% (53%) of the comedy ratings in the sample are based on more than 1,000 votes, and only 1.6% (10%) of them are based on less than 50 votes.[23] For each weekend t in the sample I construct the (simple) average IMDB rating of all comedies that are playing in that given weekend (see Table I). Such a measure proxies for the quality of the comedies to which moviegoers are exposed on a given weekend.

C. Environmental Controls

The environmental controls are constructed using data from several sources. From the behavioral finance literature I identify a set of factors that are believed to affect people's moods and, in turn, have an impact on stock returns. Following Kamstra et al. (2003), to capture the Seasonal Affective Disorder effect I construct a Fall dummy (*F*) and a *SAD* variable that measures the standardized daily hours of night in New York City. In the spirit of Yuan et al. (2006), to control for the influence of the lunar cycle, I construct a full-moon dummy (*Full*) that takes value 1 up to three days before and after each full moon date and 0 otherwise, and a new-moon dummy (*New*) that takes value 1 up to three days before and after each new moon date. In the spirit of Krivelyova and Robotti (2003), using the c9 geomagnetic index provided by the National Geophysical Data Center in Boulder (CO), I construct a dummy variable (*Geostorm*) that takes value 1 on the three days that follow a sizable disturbance in the Earth's magnetosphere (c9 index ≥ 7) and 0 otherwise. Following Cao and Wei (2004), Hirshleifer and Shumway (2003), and Keef and Roush (2002) I create a time series of daily average temperature (F°), rainfall (a dummy taking value 1 if a positive amount of rain falls on day t and 0 otherwise), and wind speed (knots) in New York City using data from the National Climatic Data Center in Asheville (NC).

Finally, to control for broad weather patterns within the U.S. borders that may influence the mood of a large fraction of the U.S. population (and, as a result, its investment decisions, leisure choices, and movie selections), I follow Dahl and DellaVigna (2009)'s approach and I construct a set of environmental controls that capture widespread hot and cold temperatures, as well as other

[23]The IMDB movie ratings were collected on June 17, 2010. The movies with a low number of IMDB votes tend to be small productions that attract small audiences.

weather features. More specifically, for the capital of each U.S. state I collect information about maximum daily temperature (F°), minimum daily temperature, maximum wind speed (knots), and six dummy variables for the daily occurrence of rain, snow, fog, hail, thunderstorms, and tornados.[24] All data are obtained from the National Climatic Data Center in Asheville (NC). I then convert the state-level temperature and wind speed variables into dummy variables as follows: three dummies are constructed for the maximum daily temperature falling in one of three classes (80 < F° ≤ 90; 90 < F° ≤ 100; F° > 100), three dummies are constructed for the minimum daily temperature falling in one of three classes (F° ≤ 10; 10 < F° ≤ 20; 20 < F° ≤ 32), and two more for the maximum wind speed falling in one of two classes (17 < knots ≤ 21; knots > 21). For each of the resulting 14 state-level weather dummy variables I finally construct a daily national weighted average using as weights the relevant state populations.[25] The resulting 14 national weather variables have an intuitive interpretation; each of them proxies for the percentage of the U.S. population that on day *t* is exposed to a particular weather phenomenon (e.g. rain, snow, high temperatures, etc).

[24]There are three exceptions. In the case of Kentucky, Maryland, and Nevada I employ weather data for Lexington, Baltimore, and Reno, respectively. This choice is guided by the availability of data.

[25]Population figures by state are taken from the U.S. Census Bureau. I assign a daily missing value to the daily national weighted average of a given weather variable when there are missing state-level data that account for more than 10% of the U.S. population. When the missing state-level weather data account for less than 10% of the U.S. population I use only the available state-level data to compute the daily national weighted average.

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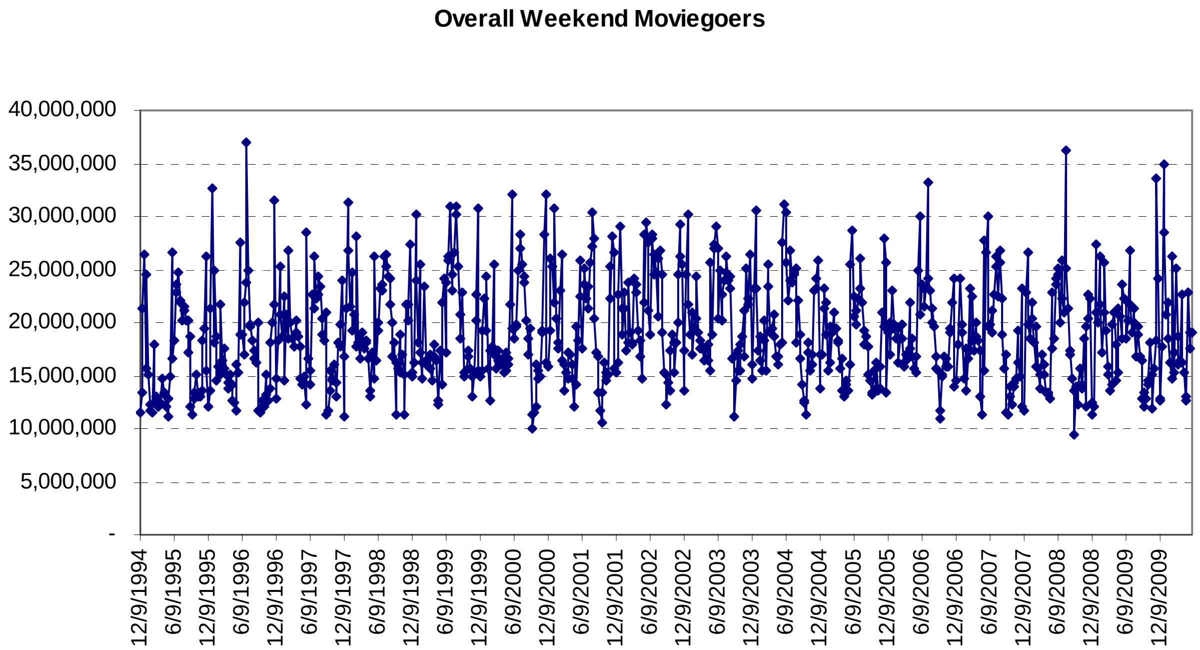

Figure 1. Plot of the total number of domestic moviegoers by weekend (Friday through Sunday). The data are obtained by deflating box-office revenues (from *www.the-numbers.com*) by the average ticket price.

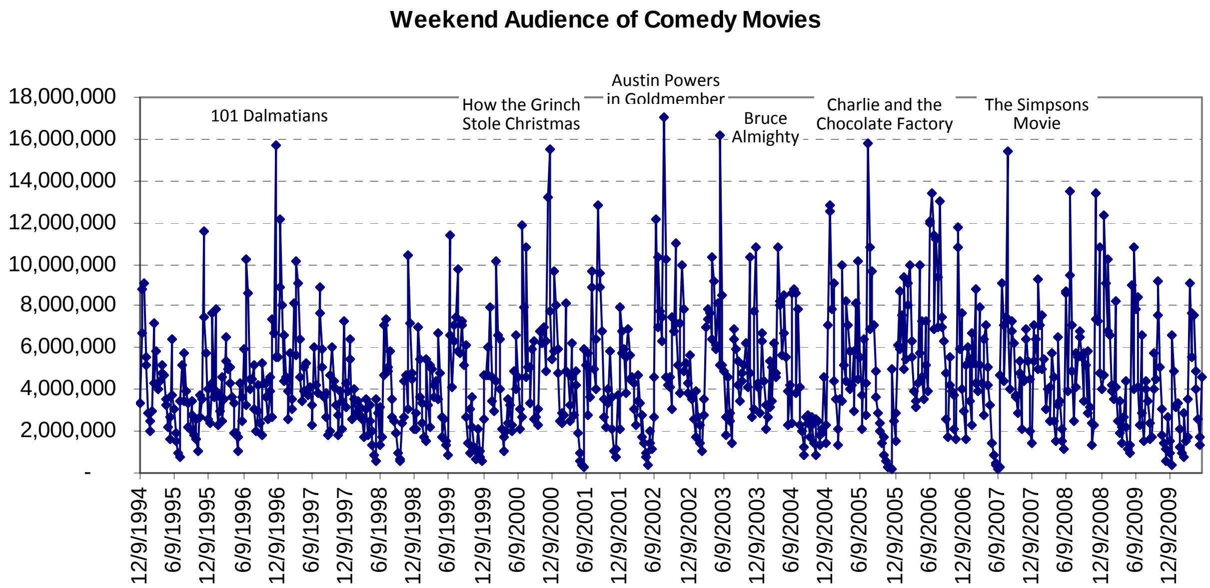

Figure 2. Plot of weekend (Friday through Sunday) audience for comedy movies in the domestic market. Movies are sorted by genre according to the classification provided by *www.the-numbers.com*. The six weekends with the largest audiences are labeled. The audience data are obtained by deflating box-office revenues (from *www.the-numbers.*com) by the average ticket price.

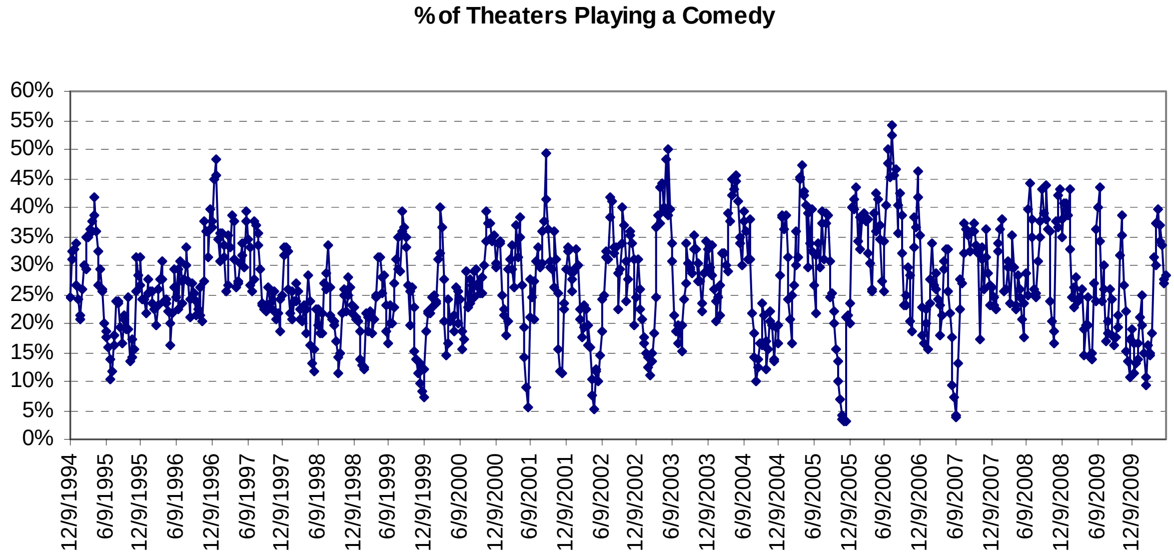

Figure 3. Plot of the percentage of domestic theaters playing a comedy movie by weekend (Friday through Sunday). Movies are sorted by genre according to the classification provided by *www.the-numbers.com*. Theater count data are obtained from *www.the-numbers.com*, which defines a theater as "any place a movie is showing from the smallest cinema on the art house circuit to the largest megaplex".

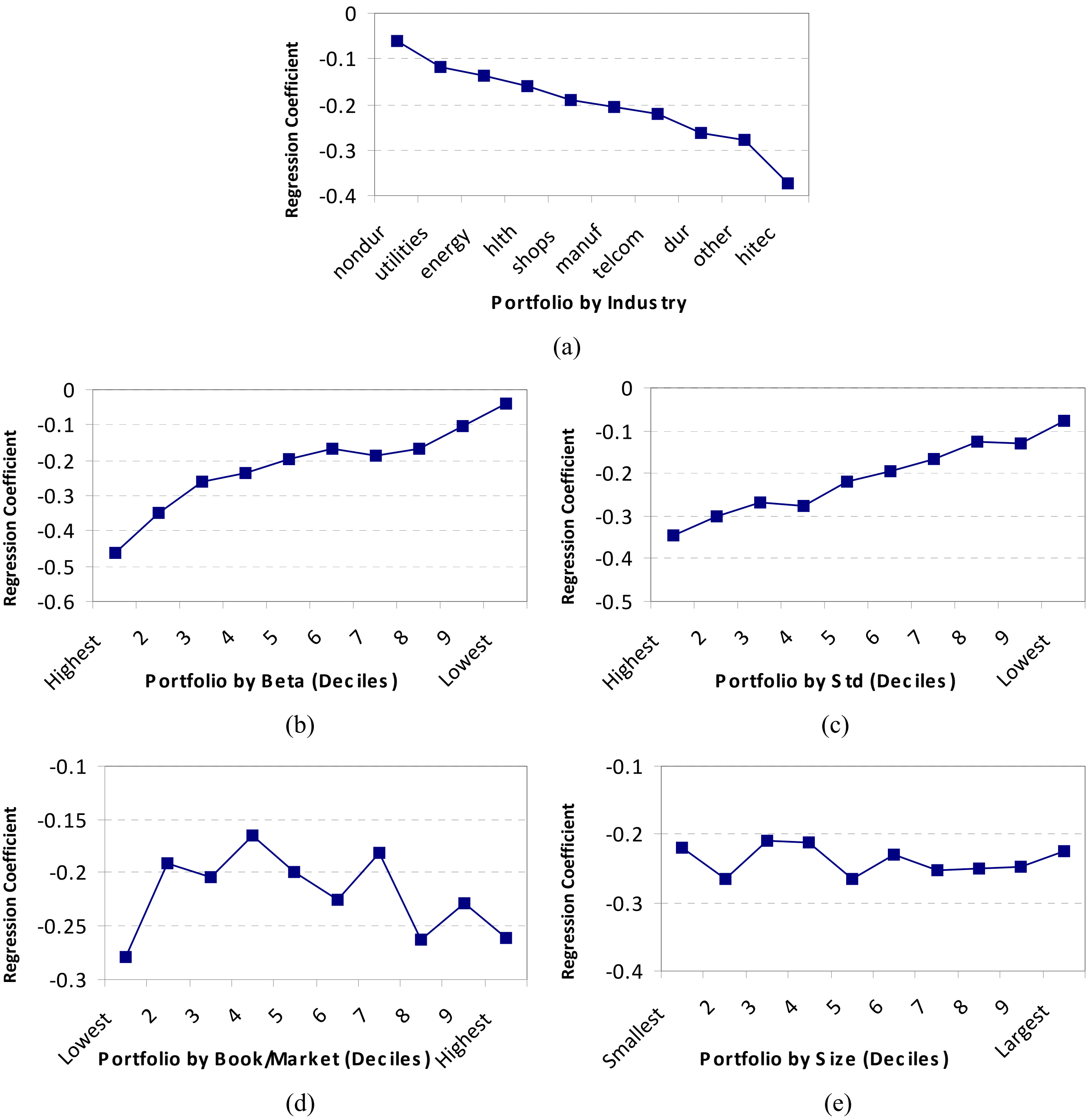

Figure 4. Movie-induced positive mood effect and firm characteristics. The figure depicts the estimated mood effect coefficient for ten Fama and French (1992) portfolios constructed by industry (panel a), book-to-market ratio (panel d), and size (panel e). It also depicts the estimated mood effect coefficient for ten CRSP portfolios constructed by beta (panel b) and standard deviation (panel c).

Table I
Movie Audiences and Theaters Count – Descriptive Statistics

Panel a of this table displays some summary statistics concerning domestic weekend movie admissions by movie genre. The sample covers a period from December 9, 1994 through May 31, 2010. Panel b shows some summary statistics about the number of theater screens allocated to different movie genres over the same period of time, and panel c displays some information about average movie ratings.

	Average	Standard Deviation	Min	Max
(a) Movie Audience for Weekends (Friday - Sunday)				
Comedy Movies	4,674,859 (808 obs.)	2,826,026	191,053	17,054,450
Thriller/Suspense Movies	1,331,654 (808 obs.)	1,567,135	0	11,909,881
Strongly Violent Movies (*kids-in-mind* rating ≥ 8)	2,307,095 (808 obs.)	2,194,059	0	14,198,758
Violent Movies (MPAA rating = R or NC-17)	5,725,918 (808 obs.)	3,020,129	132,203	17,644,444
Total Movie Audience (All Genres)	19,036,100 (808 obs.)	4,846,434	9,382,466	36,964,034
(b) # of Movie Theaters for Weekends (Friday - Sunday)				
Comedy Movies	10,203 (808 obs.)	3,669	1,072	21,176
Thriller/Suspense Movies	3,032 (808 obs.)	2,515	0	13,651
Strongly Violent Movies (*kids-in-mind* rating ≥ 8)	4,752 (808 obs.)	2,957	0	19,275
Violent Movies (MPAA rating = R or NC-17)	12,209 (808 obs.)	4,882	1,173	25,798
Total # of Theaters	37,681 (808 obs.)	4,101	25,431	48,946
(c) Average movie quality for Weekends (U.S. IMDB users' ratings)				
Comedy Movies (1= awful; 10=excellent)	6.02 (808 obs.)	0.31	4.78	7.12

Table II
Environmental Mood Triggers – Descriptive Statistics

This table reports some descriptive statistics about a set of environmental factors employed as mood controls in the empirical analysis. Panel a contains some information about daily average temperature, rain, and wind speed in New York City (LaGuardia airport) over the period December 1, 1994 through May 31, 2010. Panel b contains some information about a set of daily proxies for the fraction of the U.S. population exposed to a selection of weather events (e.g. snow, thunderstorms, extreme hot or cold temperatures) over the same period of time.

	Average	Standard Deviation	Min	Max
(a) New York weather variables				
Average Temperature in New York (F°)	55.49 (5660 obs.)	16.87	8.5	93.6
Rain in New York (dummy: yes = 1)	0.35 (5660 obs.)	0.48	0	1
Average Wind Speed in New York (knots)	9.56 (5660 obs.)	3.38	1.8	25.4
C9 Geomagnetic Index (0-to-9 scale)	2.20 (5661 obs.)	2.08	0	9
(b) U.S. weather variables				
Snow (fraction of U.S. population exposed to)	0.07 (5655 obs.)	0.11	0	0.58
Rain (fraction of U.S. population exposed to)	0.31 (5655 obs.)	0.16	0	0.91
Fog (fraction of U.S. population exposed to)	0.28 (5655 obs.)	0.19	0	0.94
Hail (fraction of U.S. population exposed to)	0.001 (5655 obs.)	0.01	0	0.13
Thunderstorm (fraction of U.S. population exposed to)	0.09 (5655 obs.)	0.1	0	0.56
Tornado (fraction of U.S. population exposed to)	0.0003 (5655 obs.)	0.005	0	0.16
High Max Temperature (F° >100) (fraction of U.S. population exposed to)	0.02 (5655 obs.)	0.04	0	0.31
High Max Temperature ($90 < F° \leq 100$) (fraction of U.S. population exposed to)	0.11 (5655 obs.)	0.16	0	0.89
High Max Temperature ($80 < F° \leq 90$) (fraction of U.S. population exposed to)	0.23 (5655 obs.)	0.22	0	0.91
Low Min Temperature ($F° \leq 10$) (fraction of U.S. population exposed to)	0.02 (5655 obs.)	0.06	0	0.56
Low Min Temperature ($10 < F° \leq 20$) (fraction of U.S. population exposed to)	0.05 (5655 obs.)	0.09	0	0.61
Low Min Temperature ($20 < F° \leq 32$) (fraction of U.S. population exposed to)	0.15 (5655 obs.)	0.18	0	0.79
High Max Wind Speed ($\text{knots} > 21$) (fraction of U.S. population exposed to)	0.06 (5655 obs.)	0.08	0	0.65
High Max Wind Speed ($17 < \text{knots} \leq 21$) (fraction of U.S. population exposed to)	0.13 (5655 obs.)	0.09	0	0.56

Table III
Exposure to Comedy Movies and Stock Returns – Baseline Model

This table displays a subset of the coefficient estimates for regression [1] and [2]. The intercept and the coefficients on the five lagged returns are not reported due to space limitations. Newey-West standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t + \\ + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \varepsilon_t$$

Dep. Var.:	Equal-Weighted Returns	Value-Weighted Returns	Equal-Weighted Returns	Value-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.1219** (0.0586)	-0.1232* (0.0687)	-0.1234** (.0579)	-0.1183* (0.0676)
$\beta_{Moviegoers}$			0.019 (0.179)	-0.060 (0.209)
γ_{Monday}	1.659* (0.887)	1.812* (1.038)	1.363 (3.072)	2.745 (3.590)
γ_{Tax}	0.270* (0.154)	0.048 (0.172)	0.270* (0.155)	0.049 (0.172)
Observations	3794	3794	3794	3794
F statistic	6.43	1.06	5.79	0.95

Table IV

Exposure to Comedy Movies and Stock Returns – Controlling for Seasonality

This table displays a subset of the coefficient estimates for regression [3]. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. Newey-West standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t + \\ + \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \sum_{k=1}^{11} \gamma_{2k} Month_{kt} + \varepsilon_t$$

Dep. Var.:	Equal-Weighted Returns	Value-Weighted Returns
	(1)	(2)
β_{Comedy}	-0.1211**	-0.1133*
	(0.0587)	(0.0682)
$\beta_{Moviegoers}$	0.028	-0.063
	(0.184)	(0.216)
γ_{Monday}	1.175	2.705
	(3.175)	(3.713)
γ_{Tax}	0.226	0.101
	(0.162)	(0.182)
Observations	3794	3794
F statistic	3.26	0.90

Table V

Exposure to Comedy Movies and Stock Returns – Controlling for Environmental Mood Triggers

This table displays a subset of the coefficient estimates for regression [4]. The intercept, the coefficients on the five lagged returns and monthly dummies, and the coefficients on the environmental mood proxies are not reported due to space limitations. Newey-West standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

$$R_t = \alpha + \beta_{Comedy} M_t \times \ln(Comedy_{t-1}) + \beta_{Moviegoers} M_t \times \ln(Moviegoers_{t-1}) + \gamma_{Monday} M_t +$$
$$+ \gamma_{Tax} Tax_t + \sum_{j=1}^{5} \gamma_{1k} R_{t-k} + \sum_{k=1}^{11} \gamma_{2k} Month_{kt} + X_t^{'} \delta + \varepsilon_t$$

Dep. Var.:	Equal-Weighted Returns	Value-Weighted Returns
	(1)	(2)
β_{Comedy}	-0.1174**	-0.1119*
	(0.0579)	(0.0676)
$\beta_{Moviegoers}$	-0.008	-0.078
	(0.188)	(0.219)
γ_{Monday}	1.728	2.934
	(3.217)	(3.762)
γ_{Tax}	0.185	0.081
	(0.166)	(0.193)
Environmental mood triggers	X	X
Observations	3783	3783
F statistic	2.08	0.87

Table VI

Exposure to Comedy Movies and Stock Returns – IV Estimation (Equal-Weighted returns)

This table displays a subset of the coefficients resulting from estimating model [3] by 2SLS and using the benchmark instrument for *Comedy*. The CRSP Equal-Weighted returns represent the dependent variable. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

Dep. Var.:	Equal-Weighted Returns	Equal-Weighted Returns	Equal-Weighted Returns	Equal-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.2189** (0.0993)	-0.2235** (0.0988)	-0.2192** (0.0982)	-0.2147** (0.0988)
$\beta_{Moviegoers}$	0.092 (0.156)	0.629* (0.332)	0.645* (0.348)	0.689* (0.380)
$\beta_{Violent}$			0.029 (0.021)	0.067* (0.038)
$\beta_{Thriller}$			-0.012 (0.015)	-0.017 (0.035)
γ_{Monday}	1.586 (2.523)	-7.321 (5.352)	-7.902 (5.693)	-9.166 (6.539)
γ_{Tax}	0.229 (0.161)	0.212 (0.161)	0.212 (0.161)	0.214 (0.162)
Instrumenting for *Comedy*	X	X	X	X
Instrumenting for *Moviegoers*		X	X	X
Instrumenting for *StronglyViolent* and *Thriller*				X
Observations	3794	3794	3794	3794
F statistic	5.79	5.68	5.23	5.24
Endogeneity test (C-statistic)	2.74*	5.46*	5.30*	7.14
Kleibergen-Paap Wald rk F statistic	256.2	129.1	114.7	36.0

Table VII

Exposure to Comedy Movies and Stock Returns – IV Estimation (Value-Weighted returns)

This table displays a subset of the coefficient resulting from estimating model [3] by 2SLS and using the benchmark instrument for *Comedy*. The CRSP Value-Weighted returns represent the dependent variable. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

Dep. Var.:	Value-Weighted Returns	Value-Weighted Returns	Value-Weighted Returns	Value-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.2382** (0.1082)	-0.2442** (0.1086)	-0.2392** (0.1075)	-0.2345** (0.1026)
$\beta_{Moviegoers}$	0.019 (0.194)	0.714* (0.376)	0.695* (0.393)	0.706* (0.422)
$\beta_{Violent}$			0.022 (0.023)	0.051 (0.043)
$\beta_{Thriller}$			-0.021 (0.019)	-0.035 (0.047)
γ_{Monday}	3.231 (3.036)	-8.283 (6.076)	-8.083 (6.488)	-8.546 (7.364)
γ_{Tax}	0.105 (0.181)	0.083 (0.181)	0.082 (0.182)	0.083 (0.178)
Instrumenting for *Comedy*	X	X	X	X
Instrumenting for *Moviegoers*		X	X	X
Instrumenting for *StronglyViolent* and *Thriller*				X
Observations	3794	3794	3794	3794
F statistic	1.26	1.20	1.18	1.12
Endogeneity test (C-statistic)	3.16*	6.85**	6.48**	8.41*
Kleibergen-Paap Wald rk F statistic	258.9	129.1	114.6	39.2

Table VIII

Exposure to Comedy Movies and Stock Returns – Alternative Instruments (Equal-Weighted returns)

This table displays a subset of the coefficients resulting from estimating model [3] by 2SLS. The CRSP Equal-Weighted returns represent the dependent variable. The benchmark instrument for *Comedy* is replaced by alternative instruments (marked by an X). The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

Dep. Var.:	Equal-Weighted Returns	Equal-Weighted Returns	Equal-Weighted Returns	Equal-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.2280** (0.1054)	-0.2282** (0.1027)	-0.1697* (0.1005)	-0.2210** (0.0980)
$\beta_{Moviegoers}$	0.631* (0.334)	0.632* (0.326)	0.586* (0.322)	0.650** (0. 327)
γ_{Monday}	-7.283 (5.333)	-7.293 (5.268)	-7.405 (5.184)	-7.705 (5.221)
γ_{Tax}	0.212 (0.161)	0.212 (0.161)	0.209 (0.161)	0.211 (0.161)
Instrumenting for *Moviegoers*	X	X	X	X
ln(*Comedy*) instrumented with # of Theaters playing a Comedy	X	X		X
ln(*Comedy*) instrumented with next week and following week's # of Theaters playing a Comedy			X	X
ln(*Comedy*) instrumented with average Comedy movie quality		X	X	X
Observations	3794	3794	3794	3794
F statistic	5.53	5.59	5.44	5.61
Overidentification test (Hansen J statistic)		0.01	0.47	2.49
Kleibergen-Paap Wald rk F statistic	126.3	89.9	73.1	57.5

Table IX

Exposure to Comedy Movies and Stock Returns – Alternative Instruments (Value-Weighted returns)

This table displays a subset of the coefficients resulting from estimating model [3] by 2SLS. The CRSP Value-Weighted returns represent the dependent variable. The benchmark instrument for *Comedy* is replaced by alternative instruments (marked by an X). The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

Dep. Var.:	Value-Weighted Returns	Value-Weighted Returns	Value-Weighted Returns	Value-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.2645** (0.1169)	-0.2534** (0.1142)	-0.1885 (0.1182)	-0.2388** (0.1097)
$\beta_{Moviegoers}$	0.722* (0.377)	0.674* (0.372)	0.647* (0.371)	0.709* (0.371)
γ_{Monday}	-8.109 (6.076)	-7.483 (6.036)	-8.006 (5.927)	-8.297 (5.953)
γ_{Tax}	0.083 (0.181)	0.084 (0.181)	0.082 (0.181)	0.082 (0.181)
Instrumenting for *Moviegoers*	X	X	X	X
ln(*Comedy*) instrumented with # of Theaters playing a Comedy	X	X		X
ln(*Comedy*) instrumented with next week and following week's # of Theaters playing a Comedy			X	X
ln(*Comedy*) instrumented with average Comedy movie quality		X	X	X
Observations	3794	3794	3794	3794
F statistic	1.18	1.18	1.06	1.16
Overidentification test (Hansen J statistic)		1.24	1.14	2.94
Kleibergen-Paap Wald rk F statistic	126.3	89.8	73.0	57.5

Table X

Exposure to Comedy Movies and Stock Returns – Robustness Checks (Equal-Weighted returns)

This table displays a subset of the coefficients resulting from estimating model [3] by 2SLS using the benchmark instrument for *Comedy,* and including additional controls (marked by an X). The CRSP Equal-Weighted returns represent the dependent variable. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

Dep. Var.:	Equal-Weighted Returns	Equal-Weighted Returns	Equal-Weighted Returns	Equal-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.2168**	-0.2157**	-0.2215**	-0.2176**
	(0.0971)	(0.0989)	(0.0963)	(0.0981)
$\beta_{Moviegoers}$	0.180	0.196	0.609*	0.503*
	(0.162)	(0.174)	(0.324)	(0.281)
γ_{Monday}	0.069	-0.192	-7.029	-5.285
	(2.318)	(2.615)	(5.236)	(4.577)
γ_{Tax}	0.095	0.033	0.079	0.036
	(0.156)	(0.156)	(0.159)	(0.156)
Instrumenting for *Comedy*	X	X	X	X
Instrumenting for *Moviegoers*			X	X
Liquidity and Market Frictions Controls	X	X	X	X
Holiday Controls		X		X
TV Controls		X		X
Observations	3752	3752	3752	3752
F statistic	4.76	4.25	4.66	4.18
Kleibergen-Paap Wald rk F statistic	246.1	248.6	151.5	170.0

Table XI

Exposure to Comedy Movies and Stock Returns – Robustness Checks (Value-Weighted returns)

This table displays a subset of the coefficients resulting from estimating model [3] by 2SLS using the benchmark instrument for *Comedy*, and including additional controls (marked by an X). The CRSP Value-Weighted returns represent the dependent variable. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

Dep. Var.:	Value-Weighted Returns	Value-Weighted Returns	Value-Weighted Returns	Value-Weighted Returns
	(1)	(2)	(3)	(4)
β_{Comedy}	-0.2535**	-0.2534**	-0.2604**	-0.2563**
	(0.1079)	(0.1101)	(0.1073)	(0.1093)
$\beta_{Moviegoers}$	0.075	0.093	0.689*	0.556*
	(0.198)	(0.208)	(0.363)	(0.333)
γ_{Monday}	2.521	2.242	-7.645	-5.444
	(3.031)	(3.277)	(5.869)	(5.419)
γ_{Tax}	0.049	0.009	0.026	0.014
	(0.173)	(0.181)	(0.175)	(0.181)
Instrumenting for *Comedy*	X	X	X	X
Instrumenting for *Moviegoers*			X	X
Liquidity and Market Frictions Controls	X	X	X	X
Holiday Controls		X		X
TV Controls		X		X
Observations	3752	3752	3752	3752
F statistic	1.61	1.52	1.58	1.47
Kleibergen-Paap Wald rk F statistic	246.9	249.3	149.9	169.6

Table XII

Exposure to Comedy Movies and Stock Returns – Ten Portfolios Classified by Standard Deviation

Each row in the table reports the coefficients of a different 2SLS regression based on model [3], where the dependent variable is the value-weighted return of one of the CRSP standard deviation-based deciles for the NYSE/AMEX market combination. All regressions employ the benchmark instruments for *Comedy* and *Moviegoers*. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients (Kernel=Bartlett, bandwidth chosen based on Newey-West (1994)). One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

	β_{Comedy}	$\beta_{Moviegoers}$	γ_{Monday}	γ_{Tax}	Obs.	F statistic	Instrumenting for *Comedy* and *Moviegoers*	Endogeneity test (C-statistic)	Kleibergen-Paap Wald rk F statistic
Decile 1 (Highest std)	-0.3441*** (0.1287)	0.902** (0.404)	-10.251 (6.532)	0.600** (0.279)	3794	13.11	X	6.77**	129.0
Decile 2	-0.2994** (0.1312)	0.871** (0.434)	-10.258 (6.926)	0.321 (0.265)	3794	4.78	X	5.39*	129.3
Decile 3	-0.2671** (0.1123)	0.705* (0.418)	-7.906 (6.888)	0.119 (0.207)	3794	2.23	X	4.35	138.6
Decile 4	-0.2749** (0.1227)	0.802* (0.419)	-9.388 (6.672)	0.068 (0.193)	3794	1.64	X	4.76*	128.8
Decile 5	-0.2215** (0.1113)	0.825** (0.399)	-10.536* (6.381)	0.069 (0.173)	3794	1.62	X	5.26*	128.6
Decile 6	-0.1968* (0.1074)	0.811** (0.382)	-10.669* (6.072)	0.035 (0.157)	3794	1.59	X	5.21*	128.6
Decile 7	-0.1677* (0.0952)	0.681** (0.326)	-8.907* (5.219)	0.055 (0.147)	3794	1.59	X	5.62*	128.6
Decile 8	-0.1249* (0.0707)	0.558* (0.297)	-7.475 (4.914)	0.062 (0.115)	3794	1.79	X	6.79**	146.2
Decile 9	-0.1313* (0.0747)	0.444** (0.210)	-5.461 (3.432)	0.099 (0.079)	3794	3.45	X	6.64**	128.6
Decile 10 (Lowest std)	-0.0779 (0.0611)	0.118 (0.123)	-0.824 (2.236)	0.125** (0.057)	3794	11.15	X	4.29	129.1

Table XIII

Exposure to Comedy Movies and Stock Returns – Ten Portfolios Classified by Beta

Each row in the table reports the coefficients of a different 2SLS regression based on model [3], where the dependent variable is the value-weighted return of one of the CRSP beta-based deciles for the NYSE/AMEX market combination. All regressions employ the benchmark instruments for *Comedy* and *Moviegoers*. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients (Kernel=Bartlett, bandwidth chosen based on Newey-West (1994)). One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

	β_{Comedy}	$\beta_{Moviegoers}$	γ_{Monday}	γ_{Tax}	Obs.	F statistic	Instrumenting for *Comedy* and *Moviegoers*	Endogeneity test (C-statistic)	Kleibergen-Paap Wald rk F statistic
Decile 1 (Highest β)	-0.4604*** (0.1585)	1.069* (0.600)	-11.174 (9.763)	0.333 (0.359)	3794	2.57	X	6.65**	147.3
Decile 2	-0.3473*** (0.1314)	0.863* (0.506)	-9.345 (8.131)	0.227 (0.249)	3794	1.68	X	5.52*	146.3
Decile 3	-0.2586** (0.1249)	0.924** (0.442)	-11.671* (7.092)	0.150 (0.226)	3794	1.60	X	5.08*	128.6
Decile 4	-0.2343** (0.1121)	0.884** (0.399)	-11.339* (6.453)	0.159 (0.179)	3794	1.61	X	6.20**	133.3
Decile 5	-0.1988** (0.1008)	0.784** (0.372)	-10.208* (6.043)	0.138 (0.161)	3794	1.68	X	6.38**	135.6
Decile 6	-0.1681* (0.0915)	0.695** (0.325)	-9.158* (5.254)	0.099 (0.144)	3794	1.83	X	5.57*	128.6
Decile 7	-0.1873** (0.0885)	0.544* (0.291)	-6.343 (4.626)	0.123 (0.127)	3794	2.30	X	4.82*	129.0
Decile 8	-0.1658** (0.0754)	0.554** (0.262)	-6.811 (4.242)	0.115 (0.088)	3794	2.57	X	6.12**	132.9
Decile 9	-0.1033 (0.0641)	0.366** (0.175)	-4.621 (2.979)	0.185** (0.076)	3794	7.25	X	6.41**	130.5
Decile 10 (Lowest β)	-0.0402 (0.0419)	0.152 (0.149)	-2.059 (2.514)	0.237*** (0.079)	3794	12.10	X	4.74*	129.4

Table XIV

Exposure to Comedy Movies and Stock Returns – Ten Portfolios Classified by Industry

Each row in the table reports the coefficients of a different 2SLS regression based on model [3], where the dependent variable is the return on one of the Fama and French (1992) 10 portfolios constructed by industry. All regressions employ the benchmark instruments for *Comedy* and *Moviegoers*. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients (Kernel=Bartlett, bandwidth chosen based on Newey-West (1994)). One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

	β_{Comedy}	$\beta_{Moviegoers}$	γ_{Monday}	γ_{Tax}	Observations	F statistic	Instrumenting for *Comedy* and *Moviegoers*	Endogeneity test (C-statistic)	Kleibergen-Paap Wald rk F statistic
NoDur	-0.0624 (0.0773)	0.321 (0.298)	-4.395 (4.997)	-0.034 (0.141)	3794	1.79	X	4.82*	128.7
Durbl	-0.2626** (0.1226)	0.578 (0.519)	-5.622 (8.657)	0.468* (0.255)	3794	1.66	X	4.60*	147.3
Manuf	-0.2068* (0.1086)	0.812** (0.385)	-10.472* (6.276)	0.123 (0.182)	3794	1.70	X	6.60**	129.0
Enrgy	-0.1374 (0.1328)	0.245 (0.487)	-2.058 (7.879)	0.048 (0.244)	3794	1.35	X	3.00	129.4
HiTec	-0.3737*** (0.1319)	0.754 (0.532)	-7.004 (8.952)	0.343 (0.333)	3794	1.24	X	9.07***	144.4
Telcm	-0.2219* (0.1234)	0.581 (0.418)	-6.386 (6.945)	0.412 (0.295)	3794	1.30	X	6.31**	141.5
Shops	-0.1900* (0.1038)	0.665* (0.374)	-8.299 (6.106)	-0.019 (0.152)	3794	2.23	X	4.12	128.5
Hlth	-0.1587 (0.0970)	0.126 (0.383)	0.259 (6.384)	-0.051 (0.254)	3794	1.80	X	3.79	139.4
Utils	-0.1191 (0.1012)	0.713** (0.319)	-10.018* (5.131)	-0.131 (0.279)	3794	1.61	X	8.21**	133.0
Other	-0.2773* (0.1425)	0.899* (0.503)	-10.930 (7.969)	-0.004 (0.188)	3794	0.94	X	6.11**	128.3

Table XV

Exposure to Comedy Movies and Stock Returns – Ten Portfolios Classified by Size

Each row in the table reports the coefficients of a different 2SLS regression based on model [3], where the dependent variable is the value-weighted return of one of the Fama and French (1992) 10 portfolios formed by size. All regressions employ the benchmark instruments for *Comedy* and *Moviegoers*. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients (Kernel=Bartlett, bandwidth chosen based on Newey-West (1994)). One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

	β_{Comedy}	$\beta_{Moviegoers}$	γ_{Monday}	γ_{Tax}	Obs.	F statistic	Instrumenting for *Comedy* and *Moviegoers*	Endogeneity test (C-statistic)	Kleibergen-Paap Wald rk F statistic
Decile 1 (Smallest Size)	-0.2199** (0.1000)	0.589* (0.329)	-6.713 (5.313)	0.123 (0.134)	3794	6.67	X	5.68*	128.5
Decile 2	-0.2653** (0.1241)	0.758* (0.450	-8.796 (7.239)	-0.042 (0.175)	3794	1.81	X	5.56*	128.8
Decile 3	-0.2094* (0.1263)	0.838* (0.464)	-10.980 (7.458)	-0.122 (0.186)	3794	1.31	X	5.01*	128.8
Decile 4	-0.2122* (0.1191)	0.793 (0.426)	-10.181 (6.881)	-0.149 (0.186)	3794	1.50	X	5.20*	128.9
Decile 5	-0.2658** (0.1217)	0.911** (0.434)	-11.339 (6.980)	-0.139 (0.214)	3794	1.56	X	6.13**	128.9
Decile 6	-0.2292** (0.1103)	0.862 (0.404)	-11.057* (6.477)	-0.199 (0.178)	3794	2.04	X	6.69**	129.0
Decile 7	-0.2515** (0.1151)	0.746* (0.388)	-8.783 (6.328)	-0.107 (0.205)	3794	1.87	X	6.30**	129.0
Decile 8	-0.2497** (0.1187)	0.831** (0.401)	-10.206 (6.539)	-0.073 (0.189)	3794	1.62	X	6.80**	128.9
Decile 9	-0.2477** (0.1122)	0.777** (0.379)	-9.274 (6.135)	-0.006 (0.194)	3794	1.28	X	7.11**	128.8
Decile 10 (Largest Size)	-0.2253** (0.1053)	0.594 (0.365)	-6.538 (5.912)	0.171 (0.172)	3794	1.78	X	6.67**	129.0

Table XVI

Exposure to Comedy Movies and Stock Returns – Ten Portfolios Classified by Book-to-Market Ratio

Each row in the table reports the coefficients of a different 2SLS regression based on model [3], where the dependent variable is the value-weighted return of one of the Fama and French (1992) 10 portfolios formed by book-to-market ratio. All regressions employ the benchmark instruments for *Comedy* and *Moviegoers*. The intercept and the coefficients on the five lagged returns and monthly dummies are not reported due to space limitations. The set of environmental mood triggers is not included in the regressions, but the results reported here are robust to their inclusion. *HAC* robust standard errors are shown in parenthesis below the corresponding coefficients (Kernel=Bartlett, bandwidth chosen based on Newey-West (1994)). One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively. Returns are measured in percentage points.

	β_{Comedy}	$\beta_{Moviegoers}$	γ_{Monday}	γ_{Tax}	Obs.	F statistic	Instrumenting for *Comedy* and *Moviegoers*	Endogeneity test (C-statistic)	Kleibergen-Paap Wald rk F statistic
Decile 1 (Lowest Book-to-Market Equity)	-0.2794*** (0.1003)	0.581 (0.445)	-5.546 (7.359)	0.083 (0.197)	3794	1.07	X	8.84**	146.9
Decile 2	-0.1911** (0.0968)	0.558 (0.349)	-6.434 (5.792)	0.119 (0.183)	3794	1.27	X	7.06**	139.7
Decile 3	-0.2042** (0.0997)	0.682* (0.351)	-8.334 (5.682)	0.133 (0.159)	3794	1.52	X	8.06**	128.9
Decile 4	-0.1649 (0.1121)	0.589 (0.388)	-7.405 (6.170)	0.036 (0.224)	3794	1.16	X	5.51*	128.8
Decile 5	-0.1987* (0.1157)	0.610 (0.387)	-7.223 (6.285)	0.138 (0.163)	3794	1.13	X	5.12*	128.9
Decile 6	-0.2253** (0.1085)	0.737** (0.366)	-8.938 (5.749)	0.164 (0.174)	3794	1.25	X	6.95**	129.2
Decile 7	-0.1808* (0.1078)	0.749** (0.356)	-9.812* (5.647)	0.043 (0.165)	3794	1.07	X	6.75**	128.5
Decile 8	-0.2622** (0.1314)	0.849* (0.459)	-10.289 (7.139)	0.025 (0.187)	3794	1.12	X	4.31	129.0
Decile 9	-0.2277* (0.1352)	0.865** (0.428)	-11.063* (6.428)	0.143 (0.191)	3794	0.81	X	5.69*	129.0
Decile 10 (Highest Book-to-Market Equity)	-0.2609* (0.1371)	0.829* (0.456)	-9.958 (7.105)	0.282 (0.184)	3794	1.57	X	5.15*	128.9