Separating Media Exposure from News Content Effects on Stocks

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Abstract

How does media exposure affect the process of price adjustment to new information? I construct a dollar value measure of an event's media exposure, equal to the sum of all relevent articles, weighted by the price of their adjacent advertising space. For one detailed case, this measure is 0.57 correlated with daily volume and 0.30 with abnormal returns. Using a large sample of new drug approvals by the FDA, I test the hypothesis that post-event price drift is decreasing in the initial media exposure of positive news. I find that market participants underreact to low media exposure approvals and overreact to high ones. An extra article on the front page of The Wall Street Journal on approval day accounts for a 1.07 percentage points lower abnormal return over the five trading days following the average approval. These results suggest the existence of an optimal level of media exposure for market efficiency.

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1 Introduction

Information efficiency postulates that prices fully reflect all information available to market participants (Fama, 1970). When new information enters the market, prices adjust quickly and without trade. Information efficiency assigns no role to the number of market participants who receive the signal. Thus, the magnitude of the signal need not matter. However, if the speed of information diffusion or its prevalence among investors alters the path of price adjustment then the media can play an important role in financial markets as it amplifies news. Discussion is then no longer limited to purely public vs. purely private signals as publicity shades of gray become useful for asset pricing.

How does variation in media exposure affect the process of price adjustment to new information? Trade volume is an integral part of this process. Does media exposure change trading behavior? I define *media exposure* as the relative emphasis that is given to a news item.[1] This paper seeks to identify an effect of media exposure on the price adjustment process that is independent of news content. While more coverage of a positive event might be correlated with better future cash flow news, they are far from perfectly correlated. The popular press is not in the business of providing refined investment advice to its readers. It is in the business of selling newspapers, subscriptions and ads. Therefore, an editor might find it more beneficial to emphasize a mildly profitable life-saving new cure for AIDS that affects a small fraction of the population and keep the coverage of a highly profitable new treatment for foot fungus infections to a footnote.

I construct a *dollar value measure of an event's media exposure* equal to the sum of all relevent articles weighted by the price of their adjacent advertising space.[2] Assuming that the market for advertising space is competitive and that an advertiser maximizes the media exposure of the good that it is promoting, the price of ad space should reflect its value to the advertiser. The space that an ad occupies is a resource that is practically identical to the space that a news item occupies in terms of their media exposure. Hence, I can use advertising rates to quantify the news item's media exposure.

The media exposure index that I introduce captures the three main channels that Dyck and Zingales (2003) describe as those that allow the media to affect asset prices. First, in the presence of limited attention and limits to arbitrage activity, the wealth-weighted number of informed people matters (Merton, 1987; Shleifer and Vishny, 1997). The reason is that the few investors who have already learned the information are unable to take the extreme positions required to eliminate any arbitrage opportunities. Second, the media can serve as certifiers of

[1] I use the term 'media *exposure*' rather than 'media *coverage*' throughout the paper because it emphasizes the individuals exposed to the content rather than the actual coverage. The relevant notion of exposure is defined in the Oxford English Dictionary (1989) as "the action of bringing to public notice; the condition of being exposed to the attention of the general public, publicity."

[2] This is the first paper I am aware of to suggest advertising rates for this purpose.

information. An article published by a credible news source such as *The Wall Street Journal* can have a substantially different effect on asset prices than if the same article appeared in a tabloid because the *Journal* has a reputation for journalistic integrity. An authoritative media outlet's seal of approval can itself be an important signal that is incorporated into prices. Third, the media is a facilitator of common-knowledge. Upon reading a newspaper article, aside for its content, we also learn that others are learning this information as well. Morris and Shin (2002) develop a model in which financial market participants can rationally 'overreact' to public information so that prices diverge from fundamental values, especially when the precision of private information is high.

Under the assumption that any mispricing is transitory, all three channels predict that for positive news about an asset's future cash flow, post-event price drift, if any, should be decreasing with media exposure. The first panel of Figure 1 illustrates the benchmark information efficiency model. Prices adjust immediately and drift is zero regardless of media coverage. The second panel illustrates underreaction to news that is alleviated with more media exposure (dashed line). Media exposure speeds up the process of price adjustment and enhances market efficiency. The first two channels suggest such a positive price drift that is lower when many investors are exposed to the news. The third channel can generate a negative price drift, that is more negative for more public news. Such overreaction is illustrated in the third panel. In this case, media exposure distorts asset prices. Therefore, I conjecture the following testable alternative to the null hyposthesis of market efficiency:

Hypothesis 0. *Post-event price drift is zero.*

Hypothesis 1. *Ceteris paribus, post-event price drift is decreasing in the initial media exposure of positive news.*

To test these hypotheses, I aim to hold news content fixed to a specific event and examine variation in its media exposure. I collect a sample of new drug approvals by the U.S. Food and Drug Administration (FDA) matched with their sponsors' daily share data. I measure price drift as cumulative abnormal return (CAR) over a five day post-approval window. In addition, I query a comprehensive news database for all articles that report the approval on the same day and the next. I find a strong negative relationship between initial media exposure and post-approval CAR. This evidence is consistent with market underreaction to low media exposure events and overreaction to those with high media exposure. An interpretation of the results is that a single extra article on the front page of *The Wall Street Journal* on approval day accounts for a 1.07 percentage points lower abnormal return over the five trading days following the average approval. This corresponds approximately to one standard deviation in media exposure. Such a change in the value of the average firm in the sample means a $260 million difference in market capitalization. Thus, the economic significance of the results is nontrivial.

The post-approval price drift predictability results provide evidence of market inefficiency and allow me to reject Hypothesis 0 in favor of the alternative. However, they do not identify any causal effect of initial media exposure on this drift because media exposure can be driven by unobservables that also instigate a price-drift and because of an error-in-variables bias due the use of a proxy for its measurement. These identification problems have been largely ignored by previous work on the media and asset prices that treats media coverage as exogenous.

My identification strategy is to use predetermined variables that can crowd out approval news. Following Eisensee and Stromberg (2007), I proxy for the availability of other newsworthy material using *Olympic Games* incidence with the approval as well as daily *TV News Pressure* defined as the median (across broadcasts in a day) number of minutes a news broadcast devotes to the top three news segments in a day. I find that drug approval news are crowded out on days with a lot of other newsworthy material, as proxied by incidence with Olympic Games and TV news pressure. I then use the Olympics indicator and the news pressure index as instruments. Instrumental variables (IV) regression results suggest that initial media exposure has a negative effect on post-approval price drift, however it is statistically no different from zero. Weak instrument diagnostics fail to reject that the instruments are weak. The proxies for the availability of other newsworthy material that I use are probably too weak to identify an effect.

If the media indeed changes asset prices, it is interesting to investigate which new drug approvals receive more media emphasis. I find that firms that exhibit greater returns and volume in the days preceding the approval receive more media attention upon approval in my sample. Drugs given priority review status by the FDA receive on average $2,000 more initial media exposure. The media exposure time-series is positively autocorrelated in this sample. Such predictability in the time-series of media exposure can possibly alter investment decisions if it alters the liquidity or resale value of an asset.

Lastly, I examine trading behavior around these drug approvals to better understand the link between information dissemination and the volume of trade. I measure volume using turnover in excess of market turnover. I find that news of a drug approval lead to abnormal turnover in the drug developer's stock. Daily volume is highly positively autocorrelated. Each security has a persistent turnover level that explains most of the cross-sectional variation as indicated by the high R^2 diagnostics and the high positive t-statistics on the preceding period's cumulative abnormal turnover.

This paper focuses on a particular dimension of media influence on prices that is relatively unexplored in the literature. Specifically, I study variation in media attention given to a particular news item controlling for its content. My study builds on Huberman and Regev (2001), which studies a non-news event about EntreMed, a small traded biotechnology company. Their case study offers clear identification at the cost of limiting the focus to one observation. They document an overreaction to a prominent article that contained no news, as well as persistence

of a higher price level following the major news event. In this paper, I suggest a method to systematically quantify the relative prominence of a news item. In Section 2.3, I re-examine EntreMed's case. I find that the media exposure index captures well the difference between the initial publication in *Nature* and the later report in the *New York Times* that contained essentially the same content but had a much larger effect on the share's price and volume. Furthermore, I document a remarkable 0.57 correlation of media exposure with daily volume and 0.30 with abnormal returns in absolute value.

Earnings announcements provide a frequent and standard source of news for many firms. These allow for large sample studies of media effects. In a notable example, Dyck and Zingales (2003) use the most reputable and larger newspaper and the way it chose to cover an earnings announcement by focusing on GAAP earnings or "street" earnings. They find that media emphasis on GAAP earnings increases the sensitivity of stock prices to GAAP earnings surprises and decreases their sensitivity to street earnings, and the opposite happens when street earnings are emphasized. In addition, the impact of this reporting choice is stronger when the news source is the prominent *Wall Street Journal*.

DellaVigna and Pollet (2008) compare market reaction to earnings announcements on Friday to other days of the week. They find that Friday announcements have a 15% lower initial response and a 70% higher delayed response suggesting that investors underreact to Friday news. They attribute this to investor limited attention. For this reason, in the empirical tests below I control for Friday drug approvals. I find that media exposure of drugs approved on a Friday is lower on average.

Mitchell and Mulherin (1994) study the relation between the number of news stories reported daily by Dow Jones and measures of market activity including trading volume, the absolute value of market returns, and the sum of the absolute value of firm-specific returns. They find that the number of news stories and market activity are directly related and share common day-of-the-week patterns. They also use abnormally large front-page headlines to proxy for important news and find that such days exhibit abnormal market returns.

A related branch of research examines an orthogonal dimension of media influence by analyzing the content of articles while holding the news medium fixed. Studies such as Niederhoffer (1971), Cutler, Poterba, and Summers (1989) and Dyck and Zingales (2003) categorize news stories using human classifiers or automated procedures and then relate these categories to financial markets behavior. Tetlock (2007) is a recent example that analyzes a daily *Wall Street Journal* column and how its positive or negative tone relates to subsequent stock market returns. These studies are especially useful for understanding the ramifications that media spin or bias in its coverage has on financial markets.

2 Measuring Media Exposure

2.1 Advertising Rates

To measure media exposure, we need a way to compare the prominence of an article published on the front page of *The Wall Street Journal* to an article placed on an inner page of a small town's newspaper. I approximate the relative emphasis that a particular news item receives by the media, its media exposure, by weighing each news item by the price of its adjacent advertising space. This allows me to construct a uniform dollar value measure of media exposure and aggregate it over a period of time and across different types of publications. While this paper focuses on daily newspapers and magazines, a similar measure can be constructed for other mediums such as television and radio.

I assume that the market for advertising space is competitive and that an advertiser maximizes the media exposure of the good that it is promoting. Thus, the price of ad space should reflect its marginal value to the advertiser. Some determinants of this value include the ad's prominence, the medium's readership and to some extent its editorial reputation. The size of the ad is obviously important as it serves to capture the reader's attention. This is the quantity of space demanded by the advertiser. Advertisers pay a premium for color ads as well as for special position ads placed on the first few pages of a newspaper section. Circulation is a major determinant of ad rates, and the purchasing power of its audience is important as well. Ferguson (1983) shows that daily newspapers' ad rates are increasing not only in circulation but also in the local income per city household. Advertising space in higher longevity publications such as magazines is more expensive than daily newspapers which have a high turnover. Finally, the publication's reputation for editorial scrutiny can play a role. For example, the *New York Times* 2007 Advertising Rate Card states:

> The New York Times maintains an Advertising Acceptability Department whose function is to examine advertisements before publication to determine if they meet the standards of acceptability The Times has developed over the years.

While the *Modesto Bee*'s advertisement acceptance regulatory effort is less emphasized on its card:

> The subject matter, form, size, wording, illustrations and typography of all advertising are subject to the approval of the Publisher. The Publisher reserves the right to reject for any reason any advertisement offered for publication.

In short, the advertiser pays a premium for the *Times'* scrutiny which is important for the credibility of its content. Therefore, my measure of media exposure also captures the publication's credibility. The space that an ad occupies is a resource that is practically identical to

the space that a news item occupies in terms of their media exposure. Therefore, we can use advertising rates to quantify the news item's media exposure.

2.2 Details of the Methodology

For the price of ad space, I use the open (non-contract) display advertising rate per column-inch quoted for an ad on the same page as the article. I focus on print publications which have a fairly standardized market for advertising. Rate-cards are published yearly by each publication and collected by several agencies. My sample includes a 1998 world-wide cross-section of 726 newspapers, weeklies and monthly magazines covered by the news database. All publications have an open column-inch rate and circulation. Daily newspapers usually have a different rate for Sunday in which case they also specify Sunday circulation. Magazines quote a rate for a full black-and-white page which I convert to a column-inch rate using the magazine's layout specification. Circulation and rates are hand-collected from Editor and Publisher (1998), Gale Research (1998), Oxbridge Communications (1998), Hollis Directories (1998) and Stamm (1998). Figure 2 plots the international sample of publications and a sub-sample of U.S. daily newspapers. To reach the fifteen million readers of *Reader's Digest* an advertiser would pay the highest price per column-inch. As expected, the rate in the Indian daily, *The Hindu*, ($0.18) with its 604,802 readers is much less than the one charged by *Nature* ($53.52), even though its circulation is only 55,613 readers.[3]

For each article of interest that I can match to an ad rate, I calculate a media exposure grade ($MediaExposure$), equal to the regular weekday price per column-inch (PCI). If the article was published on Sunday and the publication has a special Sunday rate then I use it instead. Sunday rates are 20% higher on average and circulation is 38% higher on average than on weekdays. Newspapers also charge a special premium for guaranteed positions. If the article was featured on the front page of the paper then I multiply its grade by 5. Pages 2 and 3 get a 30% premium and pages 4 and 5 a 20% premium. Front page advertising is a relatively recent phenomena considered taboo by many journalists (Shaw, 2007). Thus, while the premia I assign for pages 2-5 are based on a small sample survey of newspaper's actual premiums, front page advertising rates are practically impossible to get and the premium is based on media experts' estimates and a few small newspapers that quote such a rate. In unreported tests I multiply each article's grade by its word count to proxy for the size of the article which can be important for grabbing the attention of readers. This modification adds no further explanatory power.

I am interested in an effect on asset prices which are determined in a market that is usually closed when newspapers are printed late at night. Therefore, I match pricing and volume data

[3]For a detailed discussion of newspaper advertising rate structure and terminology see Ferguson (1963) and Ferguson (1983).

of traded securities from CRSP to an aggregated $MediaExposure_t$ by summing the grades of all articles published between the previous market close and the date t market close. This way each closing price and daily volume is matched with the new media exposure which they should reflect. The news database contains many duplicate articles, mainly when it subscribes to an agency that provides it with full content articles as well as a second agency which provides abstracted articles listed under a different source code. Therefore, I omit duplicate articles which are from the same source if they are published on the same day and their headline's first three words are the same as those of a previously aggregated article.

A useful result is that future work can probably use daily newspaper rates alone to measure media exposure, making the data collection process less cumbersome. When I run the same tests but using only daily newspaper data (no weeklies or monthly magazines) the regression coefficients on $MediaExposure$ become slightly more statistically significant. This can be because weeklies and monthly magazines affect prices in different ways, because my advertising rates data on them is flawed or due to chance.

2.3 EntreMed Revisited

To assess the usefulness of the proposed measure, I next revisit a previously studied case where the media plays an important role. Huberman and Regev (2001) tell the story of EntreMed (ENMD), a small biotechnology company, whose stock price jumped on a May 4, 1998 after the Sunday edition of the *New York Times* reported EntreMed's breakthrough in cancer research on its front page. What is surprising is that the article's content contained no real news. It simply republished the findings which were published much earlier by *Nature* and in the popular press on November 27, 1997. Huberman and Regev point out that the prominence of the *Times* article possibly triggered a strong and permanent rise of EntreMed's stock price.

The abstract notion of prominence by a credible news source can be quantified using the measure of media exposure proposed above. For this purpose I examine the time-series of EntreMed's stock and its $MediaExposure$. I search the news database for all articles related to EntreMed and its cancer drug Endostatin between October 1, 1997 and December 31, 1998. Specifically, I run a full article search for "`EntreMed or ENMD or Endostatin`" and include republished news. This yields 1314 articles. Most articles are newswire and newsletter pieces for which I have no ad rates although they are without a doubt important for information dissemination. I can grade the media exposure of 544 distinct articles using the 1998 cross-section of ad rates (the rest get a 0 grade). Using EntreMed's return data from CRSP, I calculate market adjusted daily returns as defined by Brown and Warner (1985) by subtracting from the returns the returns on the equal-weight market portfolio.

The media exposure measure is a measure of magnitude without a sign. Therefore, Figure 3 plots the time series of EntreMed's daily market adjusted return in absolute value and its

corresponding media exposure. The first two major events are the *Nature* article and five months later the no-news *Times* article. *Nature* does not directly cause the big spike in media exposure. Rather, the popular press which covered the *Nature* article accounts for most of the $5,405 worth of media exposure that day. In contrast, the *Times* article published on Sunday, May 3, 1998 was mentioned in *Times* affiliates and other newspapers for a total of $17,280 by the time the market closed on Monday. The second largest spike in media exposure on May 18 is mostly due to extensive in depth coverage by *Time Magazine* and *Newsweek* followed by an 11.86% abnormal return. Lastly, on November 12, 1998 *The Wall Street Journal* reported on its front page that other laboratories failed to replicate Endostatin's previously reported success and EntreMed's stock dropped 24% by day's end. A regression of daily market adjusted return in absolute value on its corresponding media exposure measured in thousands of dollars yields:

$$\begin{array}{rcccccc} |MarketAdjustedReturn_t| & = & 3.72 & + & 1.48 \times MediaExposure_t & + & \epsilon_t \\ & & (1.03) & & (0.27) & & \end{array}$$

with an R^2 of 0.09. The coefficient on $MediaExposure$ is statistically significant at the 1% level and reveals that they are 0.3 correlated. Using signed returns as dependent variable in this regression yields a coefficient of 1.05 with a standard error of 0.28.

The correlation between media exposure and volume is even more striking as also illustrated by Figure 3 and the following regression:

$$\begin{array}{rcccccc} Volume_t & = & 0.18 & + & 0.23 \times MediaExposure_t & + & \epsilon_t \\ & & (0.07) & & (0.02) & & \end{array}$$

with an R^2 of 0.32. The coefficient on $MediaExposure$ is statistically significant at the 1% level and reveals a remarkable 0.57 correlation.

These results indicate that $MediaExposure$ is a good index for the quantification of media exposure that pertains to asset prices. However, establishing causality is trickier. More important events are more likely to be covered by the media. Therefore, we need to control for the content of the articles before something can be said about causal effects of the media on asset prices and volume. Nonetheless, $MediaExposure$ does capture well the difference between the initial publication in *Nature* and the later report in the *Times* which contained essentially the same information. Section 3 attempts a more ambitious identification strategy on a larger sample of stocks.

3 New Drug Approvals Event Study

New drug approvals by the U.S. Food and Drug Administration provide a convenient setting for identifying an effect of media exposure on asset prices for several reasons. First, information on

approved drugs is readily available from the FDA. Second, the event's timing is exogenous to the firm developing the drug (its sponsor). This is important since firms could otherwise time this event to maximize their share value, for example by releasing the information on a certain day of the week (DellaVigna and Pollet, 2008). Third, many public pharmaceutical companies apply for drug marketing approvals which allows for large sample studies. Fourth, a marketing approval is always a positive shock to the sponsor's future cash flow since it basically provides it with a real option on the drug's production. Thus, the direction of the effect is predictable and, to some extent, the impact on future cash flow can be estimated ex-ante. Finally and importantly, the unique drug names and active ingredients allow for a free-text article search that is likely to produce only articles that discuss the approval story. This is not the case for other well-studied events such as earnings announcements whose covering articles are harder to classify. In addition, earnings announcements often include soft information pertaining to future profitability, aside from the measureable past earnings suprise.

3.1 Drug Approval Implications for the Sponsoring Firm's Value

This section briefly covers essentials of the new drug development process relevant for asset pricing. The appendix provides a more detailed description for the interested reader.

The primary uncertainty involved with new drug development is whether or not a viable product will emerge at the end of the risky process. Most chemical compounds that make it to the clinical studies stage are abandoned without obtaining the FDA's marketing approval. DiMasi (2001) documents that by the end of 1999, only 20.9% of the new chemical entities filed with the FDA from 1981 to 1992 had been approved for marketing in the U.S.

Most original drugs are registered as patents with the patent and trademark office early in their development. These patents normally expire 20 years from the date of filing. Beginning when the drug is approved and until the patent expires, the sponsor can collect monopoly rents. This study focuses on the final phase of development when the firm submits a New Drug Application (NDA) because it is argueably the one most exogenous to the developing firm. Even if conditional on filing an application, the approval was certain, the duration of the approval process can have significant implications for the sponsoring firm's value.

In fiscal year 2006, the mean (standard deviation) approval time for *standard* new drug and new biologic license applications was 26.1 (20.6) months. At the same time, *priority* NDA and BLA approval time was 7.6 (4.0) months. Therefore, one standard deviation movement away from the mean can be important for any firm and especially for smaller ones.

3.2 Sample Description

I obtain from the Drugs@FDA database all Original New Drug Approvals from January 1990 to June 2007. Unfortunately, the FDA does not disclose information about applications that were not approved or withdrawn. Many marketing approvals refer to the same drug or active ingredient but for different dosage forms. Since my identification strategy relies on the accuracy of the article search results, I only keep drugs based on an active ingredient that has never before been marketed in the United States in any form. These are marked by the FDA as Chemical Type 1 or New Molecular Entity applications. In addition, if the same drug is administered in more than one form, I keep only the first approval.

I match each drug approval with its original sponsor's daily share information from CRSP. Since the FDA's working calendar coincides with that of the U.S. financial market, event day zero is also a trading day, albeit the FDA can issue the approval letter after market close. The FDA's policy described in U.S. Food and Drug Administration (1998) is to convey this information to the applicant within one business day, at which point at least some market participants know with certainty that the drug is approved. Even though the sponsoring firm is not obliged to make this news public, the vast majority issue press-releases so that newswires and the popular press report the story within a day. In any case, it is FDA policy to make the approval letter publicly available on its web site and through a fax-on-demand system as soon as possible and no longer than three working days from approval. Nonetheless, the choice of event window involves a tradeoff between, on the one hand, clear identification of articles that discuss only news of the approval rather than media coverage of the stock market's reaction and, on the other hand, capturing all of the initial media exposure of the drug approval. As Figure 4 shows, while many news articles are written on the second day, newswires begin to report on day zero and the largest price change is on day 1. Therefore, I calculate CAR for days 0 to 1 to capture the immediate market reaction and days 2 to 6 to capture the delayed response. The pre-approval window on days -5 to -1 is used to allow for abnormal market reaction prior to the official approval that is possibly induced by better informed traders.

Finally, I use a template to construct a text search specification using the drug's name, active ingredient and approval date. For example, the drug Lamisil based on the active ingredient Terbinafine Hydrochloride and approved on March 9, 1999 has the following search specification:

Free text	((LAMISIL) or (TERBINAFINE HYDROCHLORIDE))
	and (("food and drug administration")
	or (FDA) or (F.D.A))
Date range	03/09/1999 to 06/07/1999
Search in	Full text articles
Sources	All Sources

I then calculate *Initial Media Exposure* for each approval event as the sum of all article exposure

grades on the approval day and the following one. *Subsequent Media Exposure* is similarly calculated over the post-approval time-frame.

Table 1 provides summary statistics for the 350 drug approvals. 65% of the approvals in the sample received no immediate measurable media exposure. The average initial media exposure is \$1,390 which is approximately equivalent to five *Boston Globe* regular articles. Most approvals were covered further by the print media over the subsequent business week. Firm size can play an important role in explaining abnormal returns since the impact of a new drug approval on a firm's earnings is closely related to its pre-approval earnings. The sampled firms exhibit wide variation in size measured as market capitalization one year before the approval. With an average size of \$25 billion, the findings of this study cannot be dismissed as a small or illiquid stocks phenomena. On average 19 analysts cover the sampled securities.

A variety of drugs were approved in the sampled period. 45% received priority drug review classification to speed up the process. Orphan drugs for rare diseases constitute 20% of the sample. Cancer and HIV/AIDS drugs comprise 16% and 6% respectively of the drugs for which I have indication data. Also, note that the average approval granted its sponsor with 16 years remaining of intellectual property rights from patents and 5 years of exclusivity rights by the FDA, resulting in a real option for non-trivial monopoly rents.

Table 3 provides annual averages which show that the average number of days from approval until the first mention of the approval in the news is decreasing from 1990 through 2007. Information dissemination technology has made great progress over the sampled period due mostly to the advance of the internet. However, the news database often modifies its coverage by adding and discontinuing publications. Since I cannot distinguish between a change to the actual speed with which the media operates and a technical change to the news dataset, I include year dummies in the regressions that follow.

4 Results

The efficient markets hypothesis predicts that post-approval abnormal returns should be zero on average and attributes underreaction and overreaction anomalies to a mere chance result (Fama, 1998). This paper tests it against the alternative Hypothesis 1. Specifically, I test whether the initial media exposure of drug approvals can predict post-approval cumulative abnormal returns (PACARs). I define PACAR of firm j after approval on day t as:

$$PACAR^j = \sum_{\tau=t+2}^{t+6} ret_\tau^j - ret_\tau^m \tag{1}$$

where ret_t^j is firm j's daily return and ret_t^m is that of the value-weighted market portfolio from CRSP.[4] Since it is implausible that risk preferences or discount factors systematically change over such a short horizon, any predictability of PACAR using day t information suggests that the immediate response does not reflect the fundamental value of the asset.

Using the sample averages in Table 2 we can discern several interesting features of drug approvals. The average drug approval generated a 1.22% abnormal return in the pre-approval period of trading days -5 to -1. Upon approval it returned a further 1.33% and then declined 0.46% over the subsequent five trading days. Since the standard errors of the pre-approval and approval means are small, we can reject that they are zero at usual significance levels. The post-approval drift of the average drug is statistically no different from zero. When we do not condition on any information other than the approval itself, the market's reaction is consistent with market efficiency.

However, if we condition on a certain level of initial media exposure the picture is different. In Figure 5, I split the sample into high, low and zero initial media exposure subsamples. High media exposure approvals on average exhibit a negative drift even at a longer horizon than the one I test. The initial price increase after low media exposure approvals persists for the most part. When the media initially pays no attention to the story, the average drift is positive. While these results are consistent with Hypothesis 1, the small number of observations in each subsamples and the lack of obvious controls like firm size yield large confidence intervals around the means that make the three lines statistically indistinguishable. This figure suggests the existence of an optimal level of media exposure for market efficiency. I next turn to regression analysis to better describe this feature of the data.

4.1 Media Exposure Determinants

If media exposure can alter asset prices, it is interesting to investigate which new drug approvals are likely to receive more media emphasis. While more coverage of a positive event might be correlated with better future cash flow news, they are far from perfectly correlated. An editor might find it more beneficial to emphasize a mildly profitable yet life-saving new cure for AIDS that affects a minor fraction of the population and keep the coverage of a highly profitable new treatment for foot fungus infections to a footnote.

In Table 4, I regress next period's media exposure on variables which are known in the current period. From columns (1) through (3) we can learn that firms which exhibit greater returns and volume in the days preceding the approval receive more media attention upon approval. Priority drugs received on average $2,000 more initial media exposure. Drugs that treat AIDS/HIV or Cancer, which are almost always given priority review status do not seem to be different then others in this sample. The results also suggest that drug approval news

[4] Using the equal-weighted market portfolio does not alter any of the statistical inferences that follow.

get crowded out on days with a lot of other newsworthy material, as proxied by TV news pressure and incidence with Olympic games. However, the statistical significance of these results is somewhat weak. Finally, note that consistent with the limited attention conjecture of DellaVigna and Pollet (2008), Friday approvals receive less media exposure, despite the fact that their initial media exposure usually includes two more non-trading days.

While initially the media only covers the actual approval, subsequently it might be reporting on the market's reaction to the news. Regression specifications (4) to (6) feature subsequent media exposure as dependent variable and include initial media exposure as a right-hand-side variable. Finally, we can see that the media exposure time-series is positively autocorrelated in this sample. Predictability in the time-series of media exposure can possibly alter investment decisions if it alters the liquidity or resale value of an asset.

4.2 Post-Approval Return Predictability

The main event window of interest is days 2 to 6. According to Hypothesis 1, the initial media exposure that the approval received over days 0 and 1, should lower cumulative abnormal return over this post-approval window. Identifying a price drift means that prices initially do not reflect all information available to market participants. Predicting the magnitude of this price drift using initial media exposure suggests that media exposure has to do with the amount of divergence from fundamentals.

Specification (1) of Table 5 presents OLS regression results of post-approval cumulative abnormal returns on initial media exposure that yield a coefficient that is negative with a 1% statistical significance level. One standard deviation in initial media exposure (4.14) accounts for a -0.91% change in PACAR. Based on this evidence, we can reject Hypothesis 0 in favor of the alternative Hypothesis 1. I next investigate the robustness of this result to several controls.

Firm size is positively correlated with PACAR. This is intuitive since any single drug approval does not increase a large firm's valuation much. Moreover, short-sale constraints are more severe for smaller firms which could allow mispricing to persist. Orphan drugs predict a four percent higher PACAR, while priority review does not make a statistically significant difference. I also add year fixed effects to the regressions. The results are stronger after the inclusion of these controls.

The media can have an additional impact on prices if it further exposes the news over the post-approval window. From specification (3) we can learn that such subsequent media exposure raises the stock price. If the media's role was to provide new information to the market by increasing the wealth-weighted number of informed investors then firms with better analyst coverage should be more immune to overreaction, but this is not the case in my sample. In the presence of short-sale constraints and disagreement prices might reflect more optimistic

valuations as suggested by Miller (1977). Following Diether, Malloy, and Scherbina (2002), I use dispersion in analyst forecasts as a proxy for disagreement. Including it in the regressions yields a negative yet insignificant coefficient and reduces the standard error of the initial media exposure coefficient.

In order to entertain the possibility that daily return and volume autocorrelations are driving these results, column (4) introduces controls for pre-approval and approval window abnormal returns and volume (turnover). Pre-approval cumulative abnormal turnover is positively correlated with PACAR, while approval turnover is negatively correlated with this price drift. The regression coefficients of none of the return controls is statistically different from zero. Securities that co-vary less with the market, feature more idiosyncratic risk and are less substitutable with other assets for the purpose of arbitrage. I proxy for this risk using the standard deviation of the residuals from a market model regression of past year daily stock returns on the value-weighted market portfolio. From specification (5) we can learn that it is either not important or that the proxy is a poor one.

Furthermore, to alleviate concerns that the regression results are driven by a few outliers that received extreme media exposure, specification (6) uses $log(1 + InitialMediaExposure)$ as the dependent variable. The results are robust to this modification. I also calculate Cook's Distance for each observation to check for influential points in regression specification (2). The largest Cook's Distance is 0.08 suggesting that influential observations are not driving these results. Finally, in unreported results, I examine only a subsample of drug approvals for which initial media exposure is non-zero. Using the remaining 123 approvals yields the same results with the same significance levels despite the smaller sample size.

4.3 Instrumental Variables Estimation

The post-approval price drift predictability results above provide some evidence of market inefficiency. However, they do not identify any causal effect of media exposure on the drift because media exposure is endogenous and because of an error-in-variables bias. Endogeneity arises because unobservable characteristics of the new drug can affect both its media coverage and the market's reaction to the news. The error-in-variables problem is due to the use of a proxy for media exposure measurement. These identification problems have been largely ignored by previous work on the media and asset prices that treats media coverage as exogenous. Both of these identification problems can be alleviated using instrumental-variables estimation (see Hayashi, 2000, p. 238).

Eisensee and Stromberg (2007) find evidence suggesting that U.S. relief decisions are driven by mass media coverage of disasters and that the availability of other newsworthy material crowds out this news coverage and thus alters such important policy decisions. They proxy for the availability of newsworthy material using Olympic games incidence with the disaster as

well as daily TV news pressure which they define as the median (across broadcasts in a day) number of minutes a news broadcast devotes to the top three news segments in a day. I attain broadcast times from the Vanderbilt Television News Archive to reconstruct their daily news pressure index. The Olympics indicator is set to one if the approval day is between the opening and closing of Olympic games. I use these two predetermined variables as instruments that crowd out drug approval news.

The linear IV model that I use is

$$\begin{aligned} PACAR &= M\beta_M + X\beta_X + \upsilon \\ M &= Z\Pi + \Upsilon \end{aligned} \tag{2}$$

where M is initial media exposure, X is a matrix of controls and Z is an $N \times K$ matrix containing the L excluded instruments, TV news pressure and the Olympics indicator, as well as all the included instruments in X. The identification assumption is that $E(Z\upsilon) = 0$ and $E(MZ) \neq 0$.

That incidence with Olympic games is exogenous is quite obvious. Olympic games are scheduled well in advance and will not be rescheduled because of drug approvals or their media exposure. In addition, it is implausible that the FDA will change the approval day in order to affect the sponsor's stock price. The second instrument, TV news pressure, is predetermined in the sense that it unlikely to change because of drug approvals' media exposure. An approval is rarely an interesting enough story that evening news broadcasts will feature it in their first three news segments. Even if they did, this would imply a positive correlation between initial media exposure and TV news pressure. The results of the first-stage regressions in Table 4 suggest that the opposite holds and that they are instead negatively correlated. This suggests that as intended, the news pressure index measures the availability of other stories that crowd out drug approval news.

Estimation results are in Table 6 which also provides a reference OLS regression. While the two-stage least squares specification in columns (2) to (3) suggest that initial media exposure has a negative effect on post-approval price drift, it is statistically no different from zero. When news of a drug approval are crowded out initially, they could be published on the subsequent few days. This of course is an endogenous outcome that is again motivated by the unobserved newsworthiness of the drug. I next add subsequent media exposure as a second endogenous variable to the model in column (4). Note that this system is exactly identified so that the test of overidentifying restrictions cannot be performed. Inferences are unaffected by this modification.

The tabulated first stage F-statistics are too low to reject the hypothesis that the instruments are weak. Stock, Wright, and Yogo (2002) argue that when the instruments are relevant but weak, the TSLS estimator is biased toward the probability limit of the OLS estimator. They suggest using the GMM continuous-updating estimator of Hansen, Heaton, and Yaron (1996)

to construct confidence sets that are fully robust to weak identification in nonlinear GMM. This estimator $\hat{\theta}$ minimizes the following objective function:

$$S_N(\theta) = \left[\frac{1}{N}\sum_{i=1}^{N}\phi_N(\theta)\right]' V_N(\theta)^{-1}\left[\frac{1}{N}\sum_{i=1}^{N}\phi_N(\theta)\right] \tag{3}$$

where $\theta = (\beta_M, \beta_X)$, $\phi_N(\theta) = \upsilon \otimes Z$ and $V_N(\theta)$ is a covariance matrix estimator that allows for heteroskedasticity and cross-correlation between same-day approvals (inducing nonlinearity in the model).

The GMM estimates in column (5) show that the statistical significance of the results is still low. According to Stock and Wright (2000), Theorem 3, the concentrated objective function, $S_N(\beta_M)$, evaluated at the estimate is asymptotically χ^2 distributed, allowing us to numerically invert the statistic and form an S-set confidence interval. Figure 6 plots the concentrated GMM objective function with respect to β_M. The confidence interval, includes all β_M values where the continuous-updating GMM objective function of specification (4) lies below the $\chi^2_{K-L+1,90\%}$ value. It is attained by numerically minimizing the objective function when β_M is fixed at each value plotted. The 90% confidence interval is larger than the plotted domain and clearly does not allow us to reject zero. This suggest that the instruments set is indeed rather weak, resulting in a large confidence interval, or that there is no effect of the media on post-approval drift. Nonetheless, the shape of $S_N(\beta_M)$ is encouraging since it suggests that the GMM estimator does find the global minima at -0.47.

While a cure for AIDS is almost certain to make it to the news, less important drugs might be featured or not depending on the availability of other newsworthy material. In the presence of heterogeneous effects of the media on post-approval drift, IV regressions estimate the effect for the marginal drug approvals group that are (or are almost) crowded out of the news by the instruments. The estimated effect of initial media exposure for this subgroup is more than twice the average effect estimated by OLS.

In short, the proxies for the availability of other newsworthy material which I use as instruments are probably too weak to identify a causal effect of the media in this case.

4.4 Approval and Pre-Approval Returns

The above evidence is focused on the predictable drift in stock prices in the post-approval window. While such predictability is sufficient to reject market efficiency, a hypothesis of overreaction that is increasing with media exposure necessitates a price increase before the decline.

Table 7 presents both OLS and TSLS regression results that investigate the relationship between initial media exposure and abnormal returns during and before the approval. The

results in the first three columns use approval CAR as dependent variable. They do not allow us to statistically reject that the media has no effect on the immediate market response. Pre-approval CAR in columns (4) to (6) is positively correlated with initial media exposure, but again, the statistical significance of the results is weak. In fact, the only feature of the data we can describe with confidence is that pre-approval and approval CAR are lower for larger firms.

A price increase immediately before the approval is not necessarily indicative of insider trading. When the FDA files an NDA it designates a review goal date that is often made public at that time. Therefore, at least some investors can anticipate an announcement by the FDA of approval, postponement or rejection of the drug. The puzzle is why such increases are associated with high media exposure at approval time. One explanation is that better informed traders bid up prices before the approval in anticipation of the approval and its predictable media coverage. If such agents foresee the approval announcement, they might be willing to buy larger positions if they expect better media exposure when the FDA publicly announces the approval.

A second explanation is that excess returns and volume prior to the approval draw journalists' attention who are then ready to cover the approval story. This explanation is supported by evidence on media exposure determinants which I turn to next.

4.5 Volume Behavior Around New Drug Approvals

The focus so far has been on the path of prices and returns. But these are the outcome of trading activity in a market. In light of the strong correlation between EntreMed volume and media exposure that I find in Section 2.3, I next investigate the relationship between media exposure and trade volume around drug approval news. I construct measures of cumulative abnormal turnover (CATO) that is in excess of market turnover. As Lo and Wang (2000) discuss, many measures of volume have been used in the literature. The one I use is consistent with the Tkac (1999) model where each firm's turnover is on average equal to the market portfolio's turnover. Thus, for example, post-approval cumulative abnormal turnover is:

$$PACATO^j = \sum_{\tau=t+2}^{t+6} turnover_\tau^j - turnover_\tau^m \tag{4}$$

where $turnover_t^j$ is firm j's daily dollar volume over market capitalization and $turnover_t^m$ is that of the market portfolio from CRSP.

Historical daily turnover is for each security the average over the year preceding the approval. As reported in Table 2, it is cross-sectionally skewed, with a mean of 0.63% and a median of 0.35%.[5] Dividing each CATO average in this table by the number of days it is cumulated over

[5]Note that I drop observations that have volume history on CRSP that is shorter than 200 trading days prior

yields 0.78% pre-approval, 1.57% on approval and 0.74% post-approval abnormal turnover. As expected, news of a drug approval lead to larger than usual turnover in the sponsor's stock.

To further understand cross-sectional differences in volume, I regress pre-approval, approval and post-approval CATO on several possible explanatory variables. I also include TSLS regressions that treat all media exposure as endogenous according to an IV model similar to (2), but with CATO as dependent variable. The regression results presented in Table 8 suggest that daily volume is highly positively autocorrelated. Each security has a persistent turnover level that explains most of the cross-sectional variation as indicated by the high R^2 diagnostics and the high positive t-statistics on the preceding period's CATO.

Initial media exposure increases the immediate turnover response, but does not seem to matter for the pre or post-approval windows. Abnormal turnover is lower for larger firms in the approval timeframe and especially before the approval window. It is possible that insider trading is more prevalent among smaller firms.

4.6 Robustness of the Results to the Measure of Media Exposure

This paper introduces a new measure of media exposure. One might reasonably wonder if some unique features of this measure are driving the results described above. To address this, I reproduce the main regression specifications used thus far, only this time I use equal-weighted article counts rather than weigh each article by an advertising rate. While one might find the new measure theoretically more appealing, the two measures are 90% correlated in this sample.

As the results in Table 9 confirm, statistical inferences are robust to changing this measure. Note that the article counts do not include news services such as newsletters and newswires. Including these in the count diminishes considerably the explanatory power of the variable. The reason could be that the audience of these news services is quite different from the audience of the popular press. In unreported results I attempt to use a simple indicator that is set to one if and only if at least one article covers the news. The statistical significance of the results diminishes considerably. It seems that news aggregation is of first-order importance while the weighting scheme is less important.

5 Conclusion

The results detailed above are consistent with an effect of media exposure on asset prices that causes market under or over-reaction to public information releases where prices differ from fundamental financial values. If observable media exposure has a predictable effect on the initial reaction of the market to news then market participants should price it ex-ante, when the

to the approval. Including these observations does not alter statistical inference.

news is published, so that the anomaly would vanish. Nevertheless, the price drift phenomena that I document is relatively short-lived. Market efficiency is likely a good approximation over longer horizons where idiosyncrasies such as extreme media exposure events might matter less or when investors only have incomplete information about an asset's value.

One implication of these results is the existence of an optimal level of media exposure for market efficiency. I know of no theoretical model that solves for the socially optimal fraction of a population to be exposed to a signal. Whether a decentralized media industry can attain this optimal level is then an interesting question. A negative answer could suggest a need to regulate media coverage in order to improve resource allocation decisions in markets.

I presented evidence that the media indeed influences the prices of publicly traded pharmaceutical firms when their drugs are approved by the FDA. While a leap of faith is required in order to infer anything about other public releases of information in financial markets, my sample does allow for clear identification that is hard to achieve with large samples of events such as initial public offerings and earnings announcements.

Finally, the new measure of media exposure suggested above can be used to study empirically the effects of other news events on a variety of interesting economic phenomena such as those explored in the literature on media and public policy and on media bias.[6] Variation in media exposure given to news, while controlling for its content, has been largely ignored and could provide fertile ground for future research.

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[6]Some leading examples include Dyck and Zingales (2003), Stromberg (2004), Gentzkow (2006), Gentzkow and Shapiro (2006) and Eisensee and Stromberg (2007).

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A Appendix - The New Drug Development Process

The U.S. Food and Drug Administration's Center for Drug Evaluation and Research (CDER) mission is to promote and protect the public health by ensuring that safe and effective drugs are available to Americans.[7] Before CDER approves a drug for marketing in the U.S., the drug's sponsor must demonstrate that it is safe and effective for the treatment of its specific designated disease. Figure 7 illustrates the steps that the process mandates. Each step is conditional on the success of the previous step. It starts with laboratory and preclinical animal testing. These are followed by an investigational new drug (IND) application to the FDA which determines whether the drug can move to the clinical trials stage.

Phase 1 clinical studies are small-scale and closely monitored studies usually conducted in 20-80 healthy volunteer subjects. Their chief goal is to determine the metabolic and pharmacologic actions of the drug in humans and any side effects associated with increasing doses. Phase 2 studies are typically well-controlled, closely monitored, and conducted in a relatively small number of patients, usually involving several hundred people. Their aim is to test the effectiveness of the drug for a particular indication. Phase 3 studies are expanded trails that are coordinated with the FDA in advance and usually include several hundred to several thousand people. They are intended to gather the additional information about effectiveness and safety that is needed to evaluate the overall benefit-risk relationship of the drug. Conditional on entering Phase 3, the likelihood of approval is about 75% (DiMasi, 2001).

If the clinical studies produce satisfactory results such that the developer believes the drug is likely to be approved for marketing, then it files a new drug application (NDA) with the FDA. As the shaded regions in Figure 7 that indicate 'FDA TIME' illustrate, the NDA review is the stage least controlled by the sponsor. The future of the drug is now at the mercy of an intricate bureaucratic process. Aside for its internal review process, the FDA may consult external advisory committees for difficult decisions. These public meetings are concluded by a non-binding vote by committee members. Zuckerman (2006) finds that when these meetings are scheduled, the drug will almost certainly be approved, regardless of committee recommendations.

The NDA process has several possible outcomes. The drug can be approved for marketing, in which case the FDA issues an *approved* letter granting the sponsor the legal right to begin marketing the drug effective immediately. An *approvable* letter basically means that the drug is approved, pending resolution of minor deficiencies, mostly labeling changes, and could request a commitment to do post-approval studies. These positive outcomes stand in contrast with a denial of the application or a sponsor initiated withdrawal. A denial takes the form of a *not approvable* letter. Withdrawn applications can be the result of communication between the FDA and the sponsor during the review process indicating that it is likely to be denied. Table

[7] All information is from Center for Drug Evaluation and Research (1998) and other Food and Drug Administration publications available at http://www.fda.gov.

10 shows a breakdown of the actions first taken by the FDA following an NDA submission. During the 1993-2005 period, the likelihood of an NDA approval is at minimum 75.4% on average. This number is a lower bound on the probability of approval conditional on entering the NDA stage since denied applications are often resubmitted.

Drugs that promise significant benefit over existing therapy for serious or life-threatening illnesses for which no therapy exists, can get *priority* review status to speed their development. These drugs can be marketed before all clinical trial phases are complete, provided that the manufacturer continue testing after approval to demonstrate the drug's effectiveness. In addition, the FDA seeks to stimulate the research, development, and approval of products that treat rare diseases that affect less than 200,000 Americans. Sponsors of such *orphan* drugs enjoy seven years of marketing exclusivity after approval. These and other incentives for innovation that the FDA grants can significantly speed-up the time-to-market of new drugs and increase the sponsors' future earnings.

Figure 1: **Theoretical Price Paths Following Positive News**

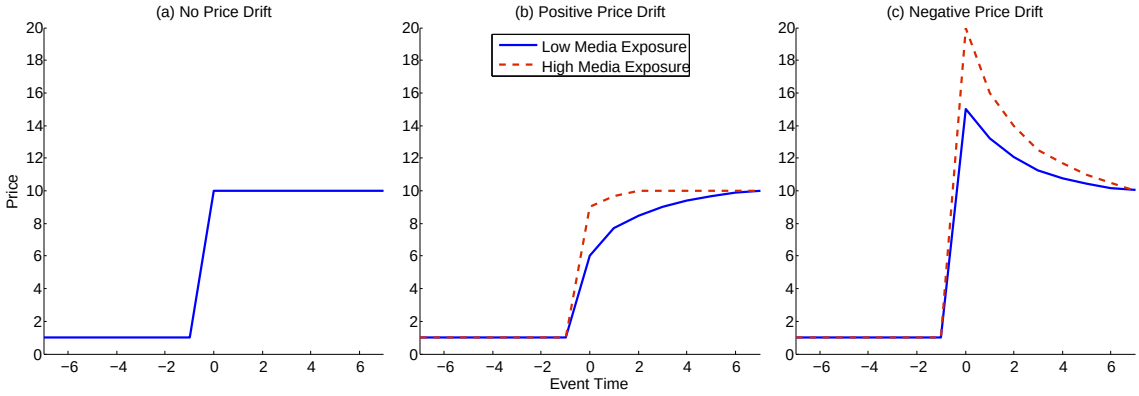
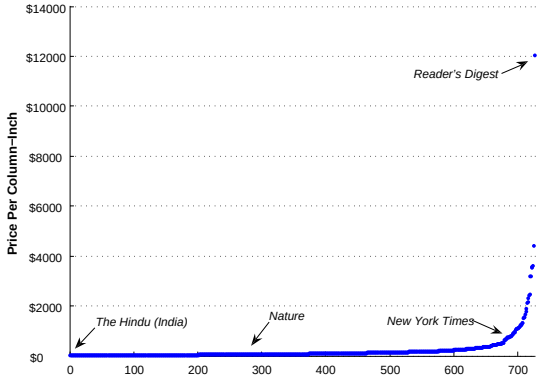


Figure 2: **1998 Advertising Rates**

(a) International Newspapers, Weeklies and Magazines



(b) U.S. Daily Newspapers

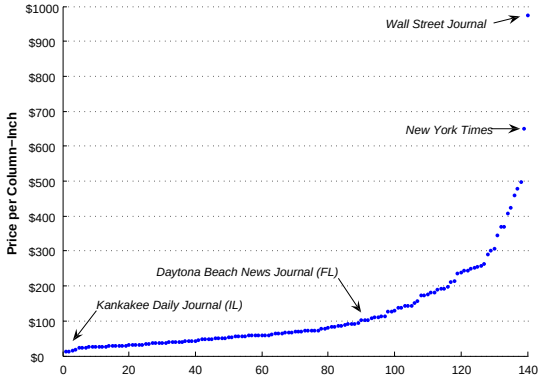
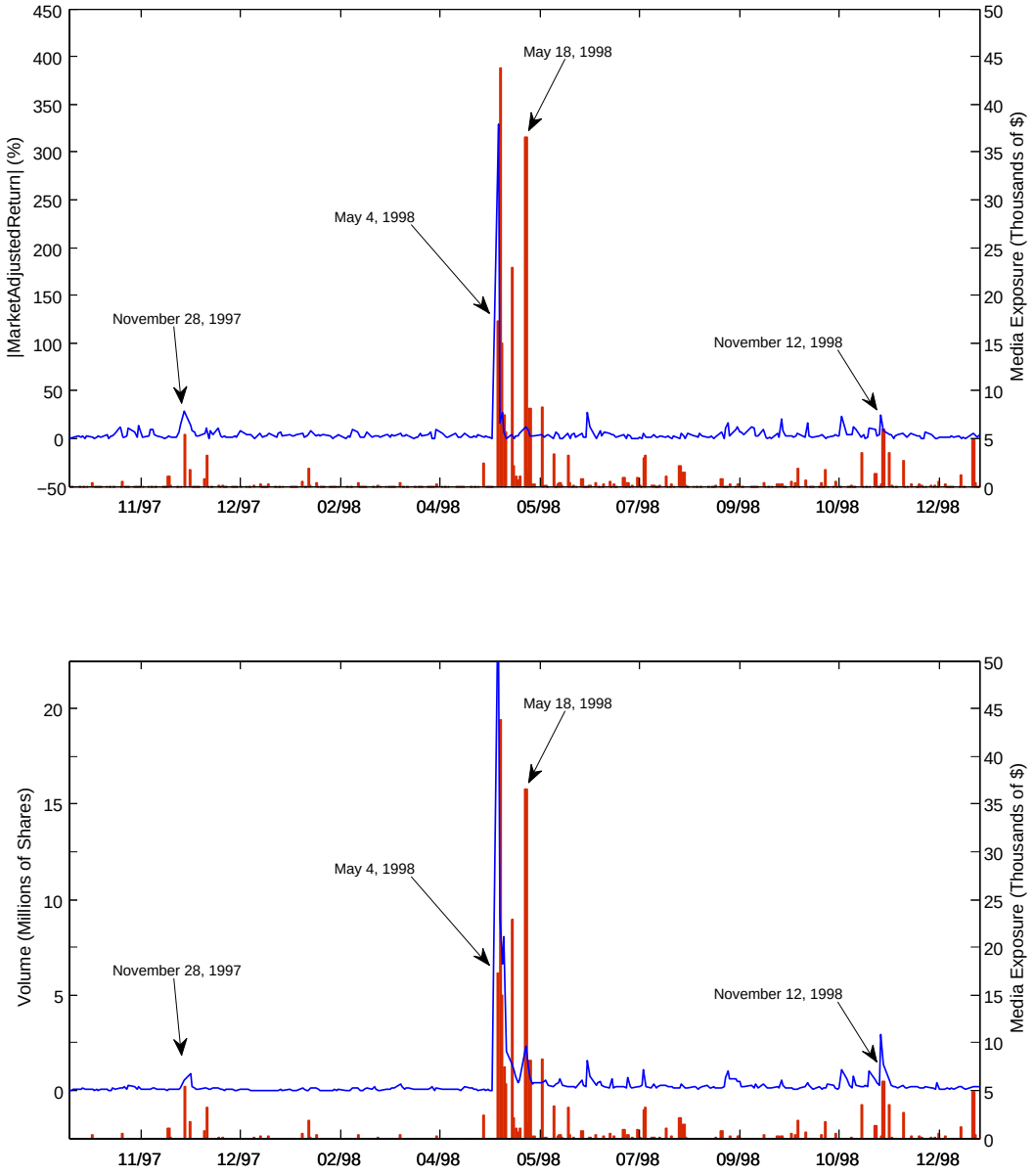
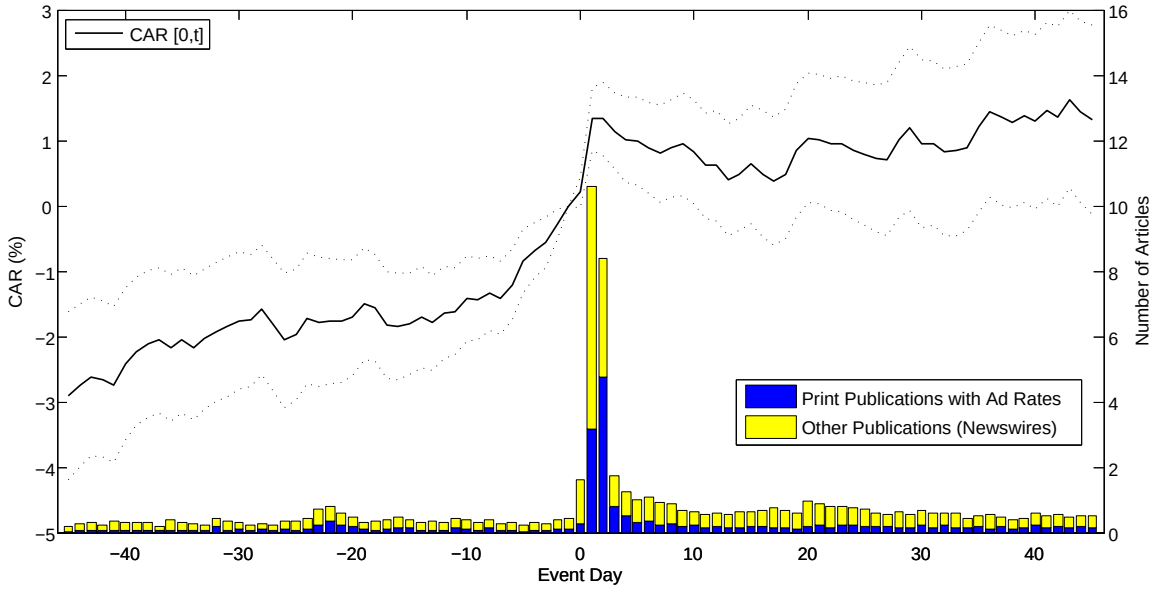


Figure 3: **EntreMed Stock Returns, Volume and Media Exposure: October 1, 1997 to December 31, 1998**



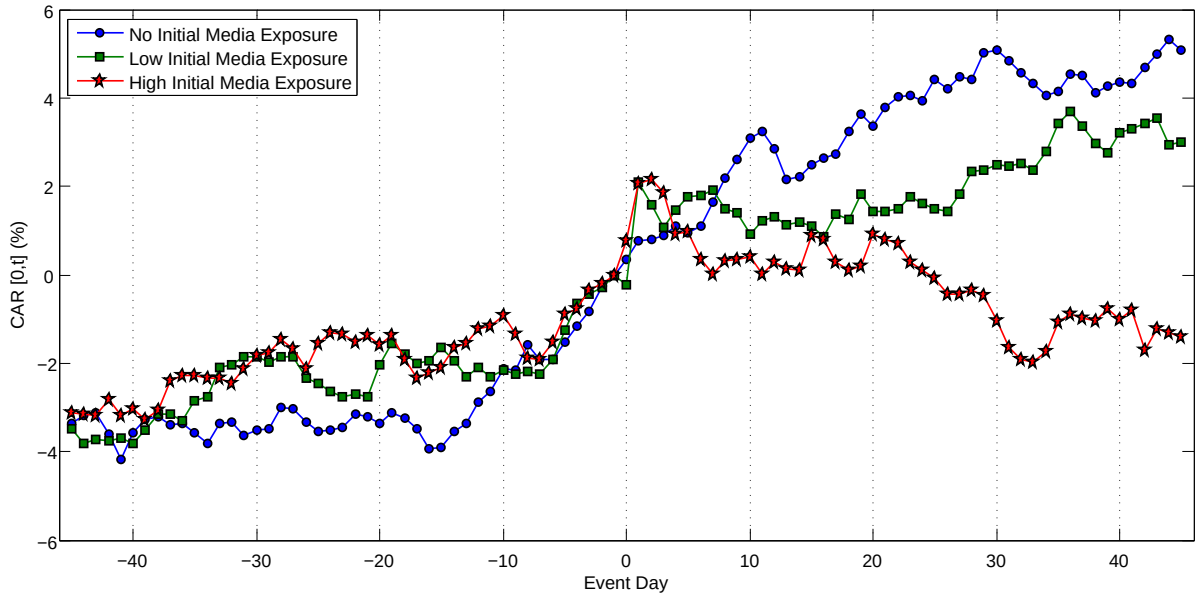
Bars represent $MediaExposure$ for day t which is the sum of all articles related to EntreMed that where published between day t-1 market close and day t market close and weighted by the relevant price per-column-inch of advertising. $|MarketAdjustedReturn|$ is the absolute value of ENMD daily return minus the equal-weight market portfolio. $Volume$ is ENMD daily trade volume.

Figure 4: **Average Cumulative Abnormal Returns and Media Exposure for New Drug Approvals**



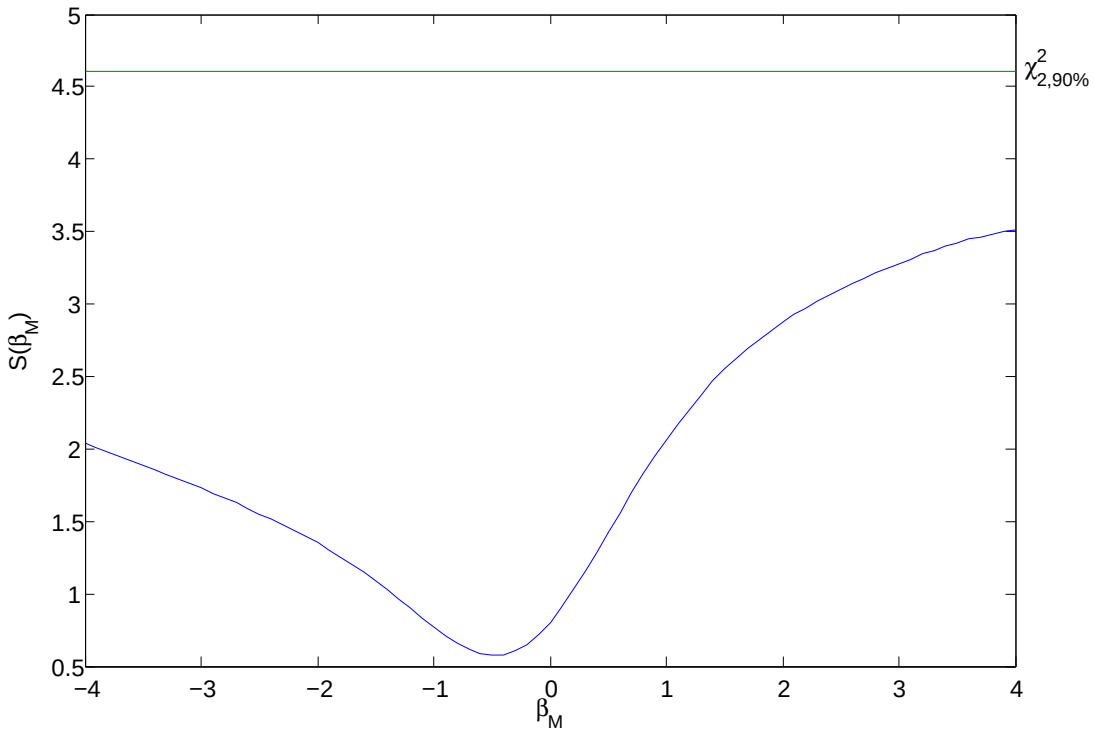
The stacked bars are the number of articles covering the new drug approval by the FDA. The dark bars are for articles for which advertising rates are available. Light bars for other publications mostly consist of news services such as newswires and newsletters. The solid line represents CAR over days [0,t]. The dotted lines are the 90% confidence interval.

Figure 5: **Initial Media Exposure Subsamples**



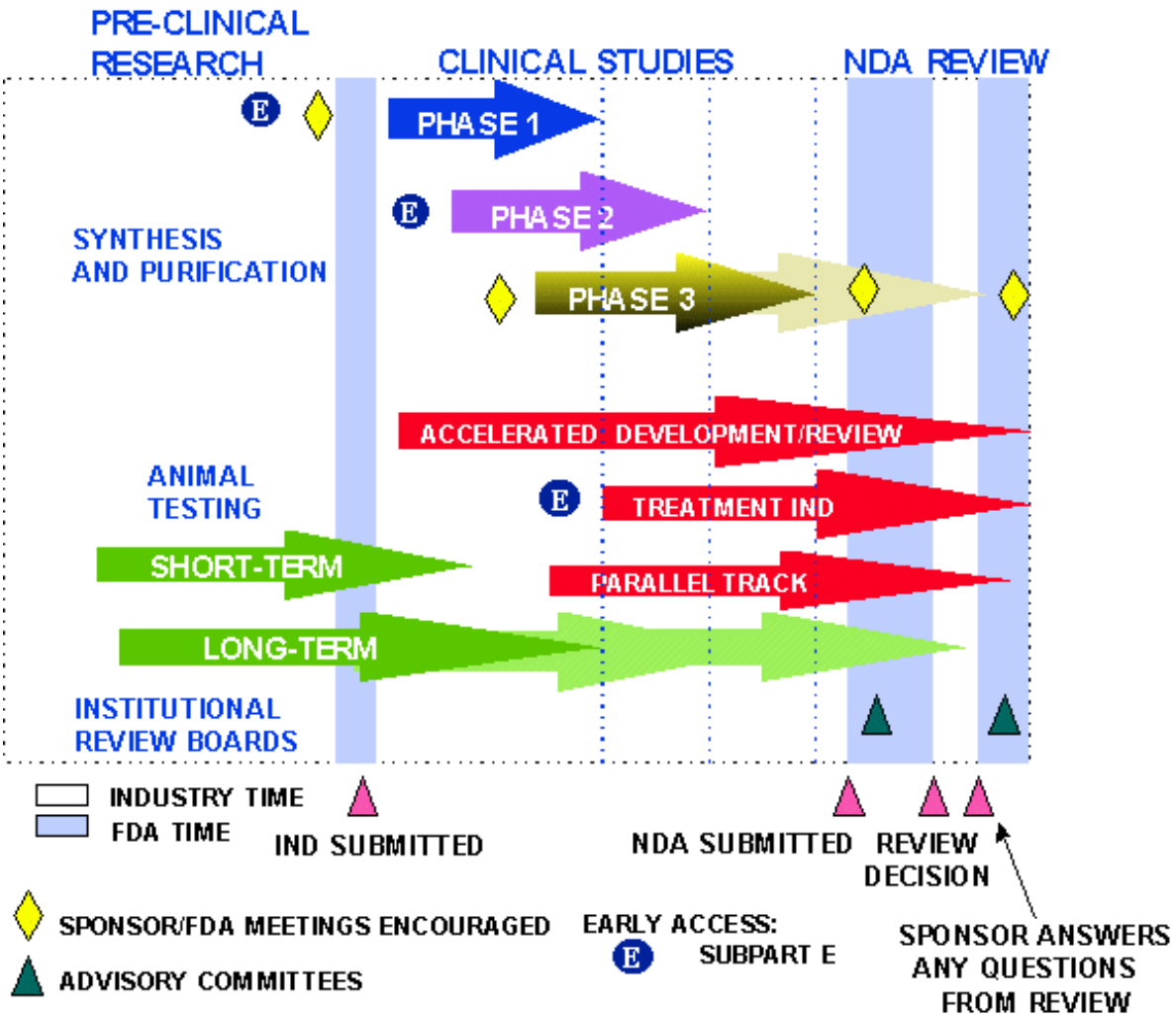
High initial media exposure subsample is the top half of drug approvals with positive media exposure containing 61 observations. Low contains the bottom 62 observations with positive media exposure. No initial media exposure subsample is 61 observations randomly selected from those without any initial media exposure.

Figure 6: **IV Concentrated Objective Function with respect to β_M**



The S-set includes all values of β_M, the coefficient on initial media exposure, where the continuous-updating GMM concentrated objective function, $S_N(\beta_M)$, of IV specification (2) in Table 6 lies below the $\chi^2_{K-L+1,90\%}$ value. It is attained by numerically minimizing the objective function when β_M is fixed at each value plotted. The nonlinearity in the model is induced by allowing for heteroskedasticity and cross-correlation between same-day approvals.

Figure 7: **The New Drug Development Process**



Source: Center for Drug Evaluation and Research (1998)

Table 1: **New Drug Approvals Sample Summary Statistics**

	Mean	Std	Min	25^{th} %	Median	75^{th} %	Max	N
Initial Media Exposure	1.39	4.14	0	0	0	0.65	31.96	350
Initial Media Exposure (Count)	3.39	8.87	0	0	0	2	70	350
Subsequent Media Exposure	2.2	3.38	0	0.02	0.97	2.69	20.92	350
Preceding Media Exposure	0.13	0.56	0	0	0	0	5.18	350
Firm Size (Millions $)	24610	43258	2	516	7132	30061	278551	350
Number of Analysts	18.93	13.78	0	6	19	30	48	350
Analysts Estimates Dispersion	0.08	0.2	0	0.01	0.03	0.06	2.41	321
Priority Drug Review	0.45	0.5	0	0	0	1	1	350
Orphan Drug	0.2	0.4	0	0	0	0	1	350
Cancer Drug	0.16	0.37	0	0	0	0	1	178
HIV/AIDS Drug	0.06	0.23	0	0	0	0	1	178
TV News Pressure	8	2.38	4	6.33	7.5	9.33	16.83	349
Olympics	0.02	0.15	0	0	0	0	1	350
Friday Approval	0.32	0.47	0	0	0	1	1	350
Idiosyncratic Risk	2.13	1.3	0.7	1.31	1.69	2.49	9.32	332
Patent Months Remaining	192.83	48.27	34.27	167.13	187.42	223.33	343.3	256
Exclusivity Months Remaining	56.8	58.08	0	0	60	90.03	213.43	256

The sample includes 350 Original New Drug Approvals over the years 1990-2007 that were marked by the FDA as New Molecular Entity applications. **Initial Media Exposure** is the sum of all articles on the approval day and the following one, weighted by an adjacent advertising rate and presented in thousands of dollars. **Subsequent Media Exposure** is calculated similarly for days 2 to 6 as is **Preceding Media Exposure** for days -5 to -1. **Initial Media Exposure (Count)** is the equal-weight aggregated number of articles. **Firm Size** is the sponsoring firm's market capitalization one year before the event in millions of dollars. If data is not available for that time then the first day with data within that year is used instead. **CAR** [a,b] is cumulative abnormal percent return over event trading days a to b, where abnormal return is return in excess of the value-weighted market portfolio. **CATO** [a,b] is cumulative abnormal percent turnover, where abnormal turnover is turnover in excess of market portfolio turnover. **Pre-Approval** window is [-5,-1]. **Approval** window is [0,1]. **Post-Approval** window is [2,6]. **Historical Turnover** is the security's past year average daily percent turnover up to day t-12 (332 observations have a long enough history). **Number of Analysts** and **Analyst Estimates Dispersion** are from I/B/E/S unadjusted summary file for one year earnings estimates valid one month before the approval. Dispersion, defined as standard deviation over absolute value of the mean, is undefined when the mean is zero or when only one analyst is covering the firm. **Priority Review Drug** and **Orphan Drug** are dummy variables set according to the drug's review classification (can both be true). **TV News Pressure** is the median (across broadcasts in a day) number of minutes a news broadcast devotes to the top three news segments on the drug approval day. **Olympics** indicates if the approval coincided with Olympic Games. **Idiosyncratic Risk** is the standard deviation of the residuals from a market model regression of past year daily stock returns on the value-weighted market portfolio (332 observations have a long enough history for the time-series regression). **Patent** and **exclusivity months remaining** are calculated as the difference between their expiry date as it appears in the FDA's Electronic Orange Book files and the approval date.

Table 2: **Returns and Volume Around Approvals**

	Mean	t-statistic	Std	Min	Median	Max	Per-day
Pre-Approval CAR	1.22	3.72	6.13	-18.07	0.61	39.13	0.24
Approval CAR	1.33	4.61	5.40	-18.61	0.63	47.08	0.67
Post-Approval CAR	-0.46	-1.50	5.73	-30.00	0.04	22.72	-0.09
Historical Turnover	0.63	15.31	0.75	0.04	0.35	6.87	0.63
Pre-Approval CATO	3.89	1.42	51.13	-4.36	-0.48	947.75	0.78
Approval CATO	3.13	2.46	23.84	-1.54	-0.08	431.80	1.57
Post-Approval CATO	3.69	1.75	39.52	-4.43	-0.31	729.63	0.74
Observations	350						

CAR [a,b] is cumulative abnormal percent return over event trading days a to b, where abnormal return is return in excess of the value-weighted market portfolio. **CATO** [a,b] is cumulative abnormal percent turnover, where abnormal turnover is turnover in excess of market portfolio turnover. **Pre-Approval** window is [-5,-1]. **Approval** window is [0,1]. **Post-Approval** window is [2,6]. **Historical Turnover** is the security's past year average daily percent turnover up to day t-12 (332 observations have a long enough history). **Per-day** is the mean divided by the number of cumulation days.

Table 3: **Annual Averages**

		CAR			Media Exposure		TV News		Days Before	
Year	Pre	Approval	Post	Pre	Approval	Post	Pressure	Olympics	First Article	N
1990	-0.20	0.08	-0.90	0.00	0.49	1.28	8.43	0.00	5.72	20
1991	1.42	0.56	-0.88	0.07	1.63	2.12	9.12	0.00	3.09	23
1992	1.09	1.66	-0.81	0.01	2.49	2.38	7.09	0.22	4.24	18
1993	0.81	-0.01	0.36	0.00	1.27	2.80	6.84	0.00	8.47	17
1994	1.49	0.73	0.24	0.00	0.10	2.22	6.56	0.00	5.86	14
1995	0.55	1.75	1.31	0.20	0.86	1.17	7.01	0.00	8.06	19
1996	0.31	1.19	0.55	0.02	0.49	1.79	7.53	0.03	4.26	39
1997	-0.20	0.89	0.82	0.03	0.07	2.20	7.27	0.00	2.18	22
1998	2.72	1.97	-1.08	0.28	2.30	2.98	8.17	0.07	2.56	27
1999	2.72	0.74	-0.79	0.11	0.47	2.29	8.27	0.00	1.35	23
2000	4.01	1.37	-2.32	0.02	1.72	1.01	8.04	0.06	3.29	17
2001	-1.61	0.90	-0.05	0.29	2.65	2.72	8.35	0.00	2.95	20
2002	2.88	2.17	-1.34	0.21	1.46	2.79	7.47	0.00	1.38	16
2003	3.46	2.21	-0.71	0.23	3.74	2.44	9.32	0.00	1.20	20
2004	0.78	3.29	-2.08	0.10	1.49	2.85	9.67	0.00	0.74	23
2005	0.62	2.80	0.68	0.02	1.16	2.02	8.55	0.00	0.85	13
2006	0.61	0.47	-1.06	0.55	1.22	2.32	7.86	0.00	0.93	14
2007	0.53	0.50	-0.97	0.99	3.16	2.01	7.43	0.00	0.00	5

Annual averages for selected variables which are described in Table 1. Days before first article is the number of calendar days from the approval day until the first mention of the approval in the news database, which includes newswires that are not measured as media exposure. Two approvals in 1990, one in 1992 and two in 1995 were never mentioned and are omitted.

Table 4: **Predicting Media Exposure**

Dependent Variable:	Initial Media Exposure			Subsequent Media Exposure		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.33	0.91	-2.60	-1.33	0.59	-4.40
	[0.55]	[0.31]	[-0.58]	[-0.76]	[0.21]	[-0.79]
Preceding Media Exposure		2.54***	2.38**			
		[2.67]	[2.48]			
Initial Media Exposure					0.13	0.23*
					[1.46]	[1.69]
log(Size)	0.11	-0.02	0.29	0.18**	0.01	0.35
	[1.21]	[-0.15]	[1.15]	[2.21]	[0.07]	[0.94]
Priority Drug Review	2.22***	1.90***	2.08***	1.46***	1.05**	0.63
	[4.30]	[3.95]	[2.80]	[3.08]	[2.01]	[0.75]
Orphan Drug	-0.15	-0.15	-0.13	-0.55	-0.24	0.37
	[-0.19]	[-0.18]	[-0.13]	[-0.98]	[-0.40]	[0.40]
TV News Pressure	-0.14	-0.14	-0.19*	-0.03	-0.01	0.03
	[-1.53]	[-1.63]	[-1.88]	[-0.38]	[-0.13]	[0.22]
Olympics	-1.75*	-2.07	-2.99	-1.01	-0.59	0.62
	[-1.78]	[-1.63]	[-1.05]	[-1.45]	[-0.72]	[0.35]
Number of Analysts		0.02	-0.06		0.04	0.01
		[0.71]	[-1.29]		[1.22]	[0.12]
Analyst Estimates Dispersion		-0.83	-1.45		0.93	1.85
		[-0.88]	[-0.75]		[1.65]	[1.32]
Friday Approval	-0.65*	-0.65	-1.08*	-0.66*	-0.55	-1.02*
	[-1.89]	[-1.64]	[-1.73]	[-1.92]	[-1.50]	[-1.71]
Pre-Approval CAR		0.10	0.12		-0.06	-0.08
		[1.16]	[1.19]		[-1.57]	[-1.38]
Pre-Approval CATO		0.01	0.20**		-0.01	0.05
		[0.51]	[2.05]		[-0.51]	[0.52]
Cancer Drug			-0.57			-1.14
			[-0.45]			[-1.35]
HIV/AIDS Drug			0.14			0.10
			[0.10]			[0.06]
Approval CAR						0.04
						[0.88]
Approval CATO						0.01
						[0.15]
Year Fixed Effects	X	X	X	X	X	X
Observations	349	320	163	349	320	163
R-squared	0.14	0.26	0.36	0.09	0.12	0.15

OLS regressions using variables defined in Table 1. t-statistics using standard errors adjusted for heteroskedasticity and clustered by approval day are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: **Predicting Post-Approval Returns**

Dependent Variable is Post-Approval CAR Over Trading Days 2 to 6						
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.16	-6.76***	-1.28	-5.35**	-3.26	-6.48***
	[-0.50]	[-2.85]	[-0.31]	[-2.36]	[-1.08]	[-2.72]
Initial Media Exposure	**-0.22*** **	**-0.21*** **	**-0.25*** **	**-0.18*** **	**-0.25*** **	
	[-3.64]	**[-3.59]**	**[-4.18]**	**[-2.62]**	**[-3.84]**	
Subsequent Media Exposure			0.17**	0.17**	0.18**	
			[2.08]	[2.13]	[2.17]	
log(Size)		0.44***	0.09	0.33**	0.24	0.44***
		[3.03]	[0.33]	[2.39]	[1.48]	[3.01]
Priority Drug Review		-1.13*	-1.45**	-1.34*	-1.31*	-1.13*
		[-1.72]	[-2.14]	[-1.96]	[-1.94]	[-1.69]
Orphan Drug		2.49**	2.83***	2.54**	2.85***	2.39**
		[2.40]	[2.69]	[2.50]	[2.72]	[2.32]
Friday Approval		-0.48	0.27	-0.23	-0.06	-0.42
		[-0.77]	[0.44]	[-0.34]	[-0.10]	[-0.67]
Pre-Approval CATO				0.09**		
				[2.20]		
Approval CATO				-0.20**		
				[-2.16]		
Pre-Approval CAR				-0.05		
				[-0.61]		
Approval CAR				0.06		
				[0.72]		
Number of Analysts			0.01			
			[0.38]			
Analyst Estimates Dispersion			-4.50			
			[-1.58]			
Idiosyncratic Risk					-0.39	
					[-0.74]	
log(1 + Initial Media Exposure)						**-0.90***
						[-1.87]
Year Fixed Effects		X	X	X	X	X
Observations	350	350	321	350	332	350
R-squared	0.02	0.10	0.13	0.14	0.11	0.09

OLS regressions using variables defined in Table 1. The Initial Media Exposure line is in bold to emphasize the main variable of interest. t-statistics using standard errors adjusted for heteroskedasticity and clustered by approval day are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: **Causal Effect of the Media on Post-Approval Drift**

Dependent Variable is Post-Approval CAR Over Trading Days 2 to 6					
	OLS	IV (TSLS)			IV (GMM)
	(1)	(2)	(3)	(4)	(5)
Constant	-6.58**	-6.35**	-6.43**	-15.73	-7.30***
	[-2.36]	[-2.04]	[-2.19]	[-0.93]	[-3.27]
Initial Media Exposure	**-0.20*** **	**-0.60**	**-0.94**	**0.28**	**-0.47**
	[-3.57]	**[-0.27]**	**[-0.89]**	**[0.10]**	**[-0.52]**
Subsequent Media Exposure				-3.56	
				[-0.53]	
log(Size)	0.42***	0.44	0.51***	1.23	0.51***
	[2.85]	[1.56]	[2.78]	[0.94]	[3.01]
Priority Drug Review	-1.06	-0.40	0.44	2.43	-0.71
	[-1.47]	[-0.09]	[0.18]	[0.40]	[-0.36]
Orphan Drug	2.41**	2.30**	2.33**	0.89	2.18**
	[2.33]	[2.16]	[2.01]	[0.26]	[2.18]
Approval CAR				0.13	
				[0.39]	
Approval CATO				0.07	
				[0.56]	
Friday Approval	-0.61	-0.68	-1.05	-2.67	-0.65
	[-0.93]	[-0.45]	[-0.97]	[-0.72]	[-0.70]
TV News Pressure	0.01				
	[0.06]				
Olympics	3.26				
	[0.89]				
Year Fixed Effects	X		X	X	X
F statistic for weak identification		3.08	1.99	0.32	1.99
Hansen J statistic		1.09	0.65	0.00	0.57
p-value of Hansen J statistic		0.30	0.42		0.45
R-squared	0.11				
Observations	349	349	349	349	349

OLS and IV regressions using variables defined in Table 1. IV regressions follow the model in equation (2) and treat all media exposure as endogenous. IV (GMM) regressions use the continuous-updating GMM estimator in equation (3) that is more robust to weak identification. The Initial Media Exposure line is in bold to emphasize the main variable of interest. t-statistics using standard errors adjusted for heteroskedasticity and clustered by approval day are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: **Explaining Approval and Pre-Approval Returns**

Dependent Variable:	Approval CAR			Pre-Approval CAR		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.02	4.90	4.84*	7.30**	-3.87	7.47**
	[1.58]	[1.04]	[1.84]	[2.30]	[-0.90]	[2.35]
Initial Media Exposure	**-0.06**	**-0.06**	**-0.73**	**0.16**	**0.20**	**-0.41**
	[-0.52]	**[-0.51]**	**[-0.93]**	**[1.21]**	**[1.31]**	**[-0.43]**
log(Size)	-0.25*	-0.41	-0.18	-0.46**	0.27	-0.39*
	[-1.88]	[-1.44]	[-1.18]	[-2.54]	[1.07]	[-1.89]
Priority Drug Review	0.99	0.60	2.46	-0.29	-0.28	0.87
	[1.54]	[0.91]	[1.36]	[-0.35]	[-0.36]	[0.42]
Orphan Drug	1.05	0.25	0.95	0.06	-0.13	-0.01
	[1.04]	[0.28]	[0.88]	[0.06]	[-0.13]	[-0.01]
Friday Approval	-0.87	-1.04	-1.30	1.16	0.89	0.82
	[-1.51]	[-1.62]	[-1.53]	[1.64]	[1.26]	[0.83]
TV News Pressure	0.09	0.18		0.01	-0.11	
	[0.59]	[1.38]		[0.07]	[-0.75]	
Olympics	1.34	1.25		2.37	3.16	
	[1.19]	[0.97]		[0.98]	[1.32]	
Number of Analysts		0.04			-0.05	
		[1.17]			[-1.32]	
Analyst Estimates Dispersion		-0.80			4.87	
		[-0.47]			[1.23]	
Pre-Approval CAR		-0.05				
		[-0.59]				
Pre-Approval CATO		-0.07				
		[-1.64]				
Idiosyncratic Risk		0.63			0.64	
		[1.09]			[1.55]	
Preceding Media Exposure					-0.31	
					[-0.53]	
Year Fixed Effects	X	X	X	X	X	X
F statistic for weak identification			1.99			1.99
Hansen J statistic			0.02			0.56
p-value of Hansen J statistic			0.89			0.46
R-squared	0.07	0.11		0.10	0.14	
Observations	349	308	349	349	308	349

OLS and IV regressions using variables defined in Table 1. IV regressions follow the model in equation (2) and treat media exposure as endogenous. The Initial Media Exposure line is in bold to emphasize the main variable of interest. t-statistics using standard errors adjusted for heteroskedasticity and clustered by approval day are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: **Volume Behavior Around New Drug Approvals**

Dependent Variable:	Pre-Approval CATO		Approval CATO		Post-Approval CATO	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	17.74**	-2.86	10.15**	3.62	2.59	-21.27
	[2.21]	[-0.07]	[2.19]	[0.83]	[0.76]	[-0.42]
Preceding Media Exposure	-0.23	26.99				
	[-0.75]	[0.24]				
Initial Media Exposure	**0.07**	**-0.84**	**0.16****	**0.16**	**-0.02**	**1.51**
	[1.07]	**[-0.45]**	**[2.15]**	**[0.41]**	**[-0.47]**	**[0.24]**
Subsequent Media Exposure					0.02	-6.97
					[0.48]	[-0.38]
log(Size)	-1.39**	-1.55	-0.71**	-0.39	-0.25	1.26
	[-2.43]	[-0.39]	[-2.45]	[-1.53]	[-1.25]	[0.39]
Priority Drug Review	0.59	-1.49	0.52	0.47	0.39	5.33
	[0.59]	[-0.09]	[1.02]	[0.46]	[0.84]	[0.44]
Orphan Drug	-0.16	-0.75	-0.09	-0.69	0.99	-1.72
	[-0.13]	[-0.20]	[-0.09]	[-1.08]	[1.42]	[-0.20]
Friday Approval	0.21	0.42	0.17	0.27	-0.04	-2.71
	[0.34]	[0.10]	[0.35]	[0.44]	[-0.13]	[-0.41]
Number of Analysts	0.16*	0.18	0.06	0.03	0.03	0.16
	[1.69]	[0.45]	[1.45]	[0.90]	[1.04]	[0.36]
Analyst Estimates Dispersion	-3.00	-1.29	-0.23	0.78	-0.25	6.22
	[-1.56]	[-0.20]	[-0.14]	[0.57]	[-0.28]	[0.31]
Pre-Approval CATO			0.43***	0.33***	0.32**	0.05
			[5.42]	[3.50]	[2.50]	[0.11]
Pre-Approval CAR			0.13	0.08	-0.12**	-0.52
			[1.60]	[1.34]	[-2.15]	[-0.38]
Approval CATO					0.59***	0.82
					[3.83]	[1.28]
Approval CAR					-0.17*	0.55
					[-1.73]	[0.30]
Historical Turnover	2.16	4.63	0.44	2.12*	0.90	5.34
	[1.26]	[1.05]	[0.71]	[1.72]	[1.35]	[0.58]
TV News Pressure	0.24		-0.05		-0.12*	
	[1.53]		[-0.46]		[-1.71]	
Olympics	2.22		1.33*		2.81	
	[1.24]		[1.84]		[1.44]	
Year Fixed Effects	X	X	X	X	X	X
F statistic for weak identification		0.03		1.76		0.07
Hansen J statistic		0.00		2.28		0.00
p-value of Hansen J statistic				0.13		
R-squared	0.27		0.54		0.76	
Observations	320	308	320	308	320	308

OLS and IV regressions using variables defined in Table 1. IV regressions follow the model in equation (2) and treat all media exposure as endogenous. The Initial Media Exposure line is in bold to emphasize the main variable of interest. t-statistics using standard errors adjusted for heteroskedasticity and clustered by approval day are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: **Robustness Tests Using Equal-Weighted Article Count**

Dependent Variable:	Pre-Approval CAR		Approval CAR		Post-Approval CAR	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-4.97	-0.58	6.39	9.17**	-0.01	-0.85
	[-1.30]	[-0.14]	[1.36]	[2.33]	[-0.00]	[-0.20]
Initial Media Exposure (Count)	**0.08**	**0.08**	**-0.05**	**-0.06**	**-0.13*** **	**-0.12*** **
	[1.18]	**[1.18]**	**[-0.95]**	**[-0.98]**	**[-2.83]**	**[-2.79]**
Subsequent Media Exposure (Count)					0.06**	0.07**
					[2.01]	[2.18]
log(Size)	0.27	0.05	-0.41	-0.54**	0.02	0.06
	[1.09]	[0.17]	[-1.45]	[-2.12]	[0.08]	[0.23]
Priority Drug Review	-0.54	-0.35	0.89	0.99	-1.39**	-1.38**
	[-0.69]	[-0.47]	[1.34]	[1.50]	[-2.08]	[-2.04]
Orphan Drug	-0.03	0.33	0.16	0.79	2.88***	2.75***
	[-0.03]	[0.35]	[0.18]	[0.72]	[2.76]	[2.68]
Number of Analysts	-0.05	-0.04	0.04	0.04	0.01	0.01
	[-1.25]	[-1.06]	[1.17]	[1.21]	[0.22]	[0.33]
Analyst Estimates Dispersion	4.74	4.92	-0.83	-1.30	-4.28	-4.10
	[1.20]	[1.23]	[-0.50]	[-0.66]	[-1.64]	[-1.62]
Friday	0.95	0.96	-1.07*	-0.93	0.82	0.45
	[1.38]	[1.41]	[-1.69]	[-1.53]	[1.31]	[0.67]
Pre-Approval CATO			-0.07		0.10*	0.13**
			[-1.57]		[1.70]	[2.54]
Approval CATO					-0.13	-0.19*
					[-1.14]	[-1.96]
Pre-Approval CAR			-0.05		-0.06	-0.03
			[-0.60]		[-0.58]	[-0.32]
Approval CAR					0.08	0.05
					[0.82]	[0.61]
Idiosyncratic Risk	0.71*		0.60		-0.13	
	[1.67]		[1.06]		[-0.21]	
Year Fixed Effects	X	X	X	X	X	X
Observations	309	321	309	321	309	321
R-squared	0.13	0.11	0.10	0.08	0.18	0.17

OLS regressions using variables defined in Table 1. The Initial Media Exposure line is in bold to emphasize the main variable of interest. t-statistics using standard errors adjusted for heteroskedasticity and clustered by approval day are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: **FDA First Actions for Original New Drug Applications**

			First Action Breakdown			
FY	Submitted	Filed	Approved	Approvable	Not Approvable	Withdrawn
1993	116	84	24	27	25	8
1994	127	92	20	28	39	5
1995	140	111	37	44	27	3
1996	123	109	50	38	20	1
1997	128	121	55	36	23	7
1998	132	114	41	39	31	3
1999	136	126	57	43	18	8
2000	133	121	46	48	17	10
2001	102	96	19	46	23	8
2002	107	96	38	46	11	1
2003	116	101	37	51	9	4
2004	132	120	58	42	15	5
2005	119	102	43	37	20	2
Total	1611	1393	525	525	278	65
% of Filed		100.00	37.69	37.69	19.96	4.67

FY is the federal fiscal year (October 1st to September 30th) in which the first action was taken. A submitted application will not be filed if it was incomplete, if fees were not received or if the application was withdrawn from filing. Data is from Food and Drug Administration (2006).