Good News Is Endogenous

Umit G. Gurun
School of Management
University of Texas at Dallas

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Abstract

Corporate board members with mass media experience influence the firm's press coverage. Compared with control firms, firms with a media expert on the board have their good news receive more media coverage and have their bad news receive less media coverage. Media coverage increases by more than 20% after hiring media experts. I show evidence that these firms suffer from an illiquidity discount of 1.2% to 3.0% per year after they hire a media expert, consistent with the argument that uncertainty about the lack/abundance of information is simply uninformative for valuation purposes.

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Contact information: Please send correspondence to umit.gurun@utdallas.edu, phone: 972-883-5917.

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"The only security of all is in a free press. The force of public opinion cannot be resisted when permitted freely to be expressed. The agitation it produces must be submitted to. It is necessary, to keep the waters pure."

Thomas Jefferson

Good News Is Endogenous

Researchers often assume that a firm's media coverage is an exogenous result of actual news about the firm. In this paper I show that firms actively manage the quantity of media coverage they receive, increasing coverage of good news and decreasing coverage of bad news. Firms do this media managing by including "media experts" on their board of directors. That is, coverage in the news media is, in part, a choice that firms make. Here is an example that describes the expectations of firms from media experts I consider in this paper:

In 1985, former Philip Morris chief executive Hamish Maxwell wrote the following in an internal memo: "A number of media proprietors that I have spoken to are sympathetic to our position – Rupert Murdoch [who was on the Philip Morris board at that time] and Malcolm Forbes are two good examples. The media like the money they make from our advertisements and they are an ally that we can and should exploit." Another Philip Morris employee stated the following in the appendix of the same memo: "Murdoch's papers rarely publish any anti-smoking articles these days."[1]

I exploit a novel dataset that allows me to infer changes in interaction between the firm and the mass media: existence of insiders (*Media Experts*) on a firm's board who have

[1] See http://www.motherjones.com/politics/1998/08/tobacco-and-rupe for the complete memo.

mass media experience at an owner/board member/editor/journalist level as a measure of the firm's willingness to actively manage relationship to media. I show that this indicator predicts future press coverage. Furthermore, I present evidence that the relation between press coverage and existing media expertise on board depends on how well the firm is performing: in good (bad) times, the firms with a media expert on board are covered more (less) than a set of control firms.

It is reasonable to expect that firms would hire media experts as board members in years they have a need for them. For example, a firm that knows a negative publicity event is coming up is more likely to seek a media expert. That is, the association between asymmetric media coverage and existence of media experts could be driven by contemporaneous events occurring in the year media experts are hired. The evidence is not consistent with this explanation: I find that the relationship between asymmetric media coverage and existence of media experts *does not attenuate* when I exclude the years media experts join the board of firms from the analysis.

How does the market interpret the "abnormal" press coverage? Given that relationship to media distorts the information availability to outside investors, the answer to this question is not *a priori* clear. There are two interpretations: On one hand, if press coverage increases the visibility of the firm and hence increases investor base, then one would expect the prices to rise to reflect the increased information availability (Merton (1987)). Under this interpretation of relation between press coverage and prices, one would expect media expertise on board to be beneficial because it reduces the discount rates. On the other hand, if press coverage is endogenously determined with existence of media experts, it is possible that information asymmetry among investors increases—i.e., the uncertainty about the lack/abundance of information is simply uninformative for valuation purposes. Asset pricing literature argues that information asymmetry should cause discount rates to rise through a liquidity channel. I present evidence consistent with the second interpretation—i.e., firms with media experts suffer an increase in cost of capital by 1.2% to 3.0% per year.

The decision to hire media experts could be endogenous to cost of capital and media coverage needs. That is, it is possible that firms are more likely to seek media experts in years they have an increase in information asymmetry events, such as reduction in voluntary disclosure by managers. If journalists are relying on the voluntary disclosure of managers to report on these firms, then reduced voluntary disclosure (e.g., an information asymmetry increasing event) would reduce coverage by newspapers regardless of any effort by media experts. To attempt to disentangle these effects, I instrument press coverage with the media experts' ownership in firms. Since media experts will spend resources in lobbying the press only if they have some skin in the game, media ownership can be considered a good measure of the exogenous component in news coverage. When I instrument coverage with this exogenous determinant, coverage's estimated impact on illiquidity does not disappear. This suggests that relationship between increased illiquidity and existence of media expert is causal.

If having media on board increases future press coverage, but dampens asset prices through the liquidity channel, why would firms actively seek such board members? A simple cost/benefit analysis would suggest that firms get something out of having such people on board. There are two possibilities: First, media expertise on board may help firms manage their media-related expenses effectively. Media experts may help hire better public relationship consultants/firms. In other words, such board members may provide connections to media and related industries (e.g., advertising, public relations). I find that the firms with media expertise are also heavy advertising spenders. Given that advertising spending is also a big revenue item for media companies, firms would benefit from media expertise on board through efficient allocation of advertising expenditures. Second, these firms may want to avoid media scrutiny due to stringent employee relations, environmental concerns, and controversial issues. In dealing with the endogeneity of hiring media experts, I find evidence consistent with this interpretation: firms that need media experts most are less likely to be desired by media experts.

The paper proceeds as follows. Section I describes background and hypothesis development. After discussing sample characteristics in section II, I present the results in Section III. Section IV concludes.

I. Background and Hypothesis Development

Although it is well established that information moves security prices, how information flows through financial markets and is impounded in the prices of financial assets is not as well understood. Models of market efficiency assume that in a frictionless market investors receive and process all relevant information; therefore, there is no obvious role for the media to affect prices.[2] However, a body of recent literature shows that investors react to attention-grabbing news by trading more of the relevant stocks and sometimes create episodes of temporary price pressures (Barber and Odean (2008) and Yuan (2008)). Under this "attention-grabbing" perspective, the media can affect asset prices not only because they select, package, and certify information (Dyck, Volchkova, and Zingales (2008)) , but also because their interest lies in going after news that is "sensational."

Another way the media can affect the prices is by providing information to a wider audience by increasing firm recognition ("visibility perspective"). Greater visibility may

[2] A related line of literature studies the affect of media on reversal of returns, trading volume and liquidity. See Chan (2003) and Gutierrez and Kelley (2008) which explores this link between trading activity and returns on news days; Chae (2005) and Chava and Tookes (2007) which analyze trading volume around news events; and Tetlock (2009) which shows that media can also release previously privately held information and help market absorb a persistent liquidity shock quickly.

increase firm value through lower expected returns and/or higher expected cash flows. Merton (1987) argues that greater investor recognition can increase the efficiency of risk sharing, which in turn will decrease (increase) the cost of capital firm value. However, greater investor recognition can also lead to higher expected cash flows through effective monitoring and greater demand for the firm's product or brand. Under this "visibility perspective," media plays a crucial role in asset prices through its coverage of firms (see Bushee and Miller (2007) and Solomon (2009)).

Gurun and Butler (2009) and Solomon (2009) show that media can affect the prices through "media slant" or "media spin." This channel suggests that firms actively manage the content of information that media reports, either though advertising dollars spent to newspapers (Gurun and Butler (2009)) or through investor relations (Solomon (2009)). Both of these papers differ from the literature that study determinants of media coverage (Fang and Peress (2009)), as both of them investigate how the media coverage can be affected by actions that firms take to actively manage relations with media. My paper belongs to this third channel by introducing the role of board members.

The first question of my paper is whether board members with media expertise are able to influence the coverage of firm in media, which I state in null form as follows:

H_0(1): A firm's media expert board members do not affect the firm's media coverage.

Next, I test a hypothesis about the influence of future media coverage on the stock liquidity. Given that relationship to media distorts information availability to outside investors, it is not a priori clear how this will affect prices. If media coverage increases the visibility of the firm, then it should increase the investor base (Merton (1987)). Consequently, one would expect prices to rise to reflect the increased information availability. Under this naive interpretation of the relation between media coverage and prices, one would expect media expertise on board to be beneficial because it reduces the discount rates. In contrast, if firms endogenously determine media coverage, it is possible that information asymmetry among investors increases. Kelly and Ljungqvist (2009) present a model, couched in the framework of Grossman and Stiglitz (1980), showing that increased asymmetry reduces prices and demand of uninformed investors. This leads to a reduction in asset liquidity. I propose the following hypothesis:

H_0(2): Managed media coverage does not affect the liquidity of the firm.

My paper contributes to two branches of the literature. In media literature, my paper is closest to those of Solomon (2009) and Bushee and Miller (2007), who study the effects of hiring investor relations firms on stock prices. In governance literature, two related papers on the value of reducing or increasing the role of corporate board members include Cohen, Frazzini, and Malloy (2009) and Guner, Malmendier, and Tate (2008). Cohen, Frazzini, and Malloy (2009) document that sell side analysts who were overly optimistic are more likely to be appointed to boards of companies they favored. Guner, Malmendier, and Tate (2008) show that board members with financial expertise are more likely to affect corporate decisions when their influence serves the interest of their own institutions.

II. Data and Methods

I use several sources to collect data on firm-specific news published by national newspapers and a newswire, a list of individuals who have newspaper media experience, advertising expenditures of firms, financial analyst following, insider ownership, and firm-specific data. I obtain stock return and accounting data from CRSP/COMPUSTAT. Financial analyst following data comes from First Call. I use 13-F filings for all reporting institutions to construct firm level institutional ownership.

II.1 Media Expertise

I obtain the names of people who have some newspaper media experience (media expert list) from the Boardex database provided by Management Diagnostic. Management Diagnostic Limited is a private research company that specializes in collection and dissemination of social network data on company officials of U.S. and European public and private companies. The query to obtain this list involves a search of more than 40,000 individual resumes to identify persons who (i) served on boards of public and/or private firms and (ii) have worked for any of the firms that can be classified under the media-newspaper category.

The media-newspaper category includes the following corporations: Tribune Company, Journal Register Company, Knight Ridder, The McClatchy Company, MediaNews Group, The Seattle Times Company, Gannett Company, Inc, Lee Enterprises, Hearst Communications, The New York Times Company, E.W. Scripts, Washington Post, and News Corporation. This list contains the top ten newspaper publisher companies according to circulation data provided by Editor & Publisher's Annual Yearbook (2006) and three other companies that have been acquired by one of these ten companies since then. As can be seen from Panel A of Table I, these 13 media newspaper publishers publish more than 350 daily newspapers, including major national newspapers such as *Wall Street Journal, USA Today, New York Times,* and *Washington Post,* as well as several regional newspapers such as *Los Angeles Times, Houston Chronicle,* and *Arizona Republic*. A conservative estimate of the circulation of newspapers owned by these media groups is that they constitute more than 90% of daily U.S. circulation as of 2008.

The number of unique names affiliated with these companies at some point in their career is 1,224, according to a snapshot of the Boardex database in 2009. The list contains several high-profile media people like Keith Rupert Murdoch (CEO and chairman of News Corporation), Donald Graham (chairman of Washington Post), Samuael Zeil (CEO of The Tribune Company), Mary Junck (CEO of Lee Enterprises), and Garry Pruitt (CEO of McClatchy Company). Media-person list does not necessarily involve C-level executives. Other titles that are commonly included in this list are “Director,” “Independent Director,” “Editor,” “Regional Editor,” and “Journalist.”

<Insert Table I here>

My next step is to identify those individuals that took some action at a public firms to reveal their information through trading. To do that, I hand-match the list of media experts to insider trading records of individuals provided by the Thompson Financial insider database to identify the list of people who have been considered to be “Level 1 or Level 2 insiders” in a public firm.[3] [4] In matching these names, I follow a conservative approach and dropped names when a clear match was not possible. In addition, I also require the media expertise to *precede* the involvement in a public firm. This is very important because by sample selection I ensure that media experts have knowledge and connections to media industry to provide the values firms expect from them.

After this step, the number of unique names dropped to 626. The reduction in sample size is due to two reasons: (1) media experts identified in Boardex may not sit on boards of

[3]Another possible approach to identify actions of media-experts is to take advantage of BoardEx database’s capabilities to identify links to other entities in the database and then search for trading records from retail brokerage houses. The lack of data is the main reason to analyze “self reported” insider trades, rather than all trades of these individuals.
[4] Level 1 and 2 insiders include the several roles including Directors and Chairman of the Boards. See TFN Insiders Manual for more details: http://wrds.wharton.upenn.edu/ds/tfn/insiders/manuals

public firms—i.e., they may sit on boards of private firms; (2) there is ambiguity in terms matching names of media experts to names in the insider trading files.

It is important to note that board members (directors) are considered to be "insiders"—i.e., those who are in a position at a firm to possess material information at the time of their involvement in public firms. My sample selection procedure excludes those individuals who have no ownership in the firm that they sit on the board of. I discuss the implications of this sample selection when I use the media expert's ownership as an instrument for media coverage in Section III.4.

<Insert Table II here>

II.2 Media Mention Measures

I collect media mentions from two national newspapers and a newswire (Dow Jones Newswire) from 1996 to 2006. The national newspapers are *Wall Street Journal* and *New York Times*. Dow Jones Newswire differs from other outlets because, unlike traditional newspapers, Dow Jones Newswire has no capacity constraint in terms of number of pages available to run stories.

In order to match news stories to other databases, I follow the procedure outlined in Gurun and Butler (2009). I use the ticker symbols, firm names, and name variants of the stocks from the CRSP database as the search strings in Factiva. The name variants we use include singular and plural versions of the following abbreviations from the company names: "ADR, CO, CORP, HLDG, INC, IND, LTD, and MFG." The search algorithm and name matching can be done in various ways. Engelberg (2008) discusses several issues regarding how to match Factiva news data to CRSP. My search algorithm first searches for capital letters within brackets (e.g., (GM) for General Motors) in the title and the lead paragraph. If no match is found, then I search for name and name variants. I use the CRSP company name change file to identify situations in which a firm changes its name. Newspapers may report on companies that are bankrupt or that will go public in an initial public offering (IPO). In order to accommodate this possibility I keep the names of firms before IPO and after delisting for an additional six-month period.

II.3 Other variables

Insider Holdings

I use Thompson Reuters Insider trading database provided by WRDS to identify the direct and indirect holdings of individuals that are identified by a unique insider id (*personid*).[5] Specifically, I use Table 1, Insider Filing data, which contains transactions and holdings information filed on Form 3 (Initial Statement of Ownership), Form 4 (Statement of Changes in Beneficial Ownership), and Form 5 (Annual Statement of Changes in Beneficial Ownership).

Advertising Measures

I use two advertising measures. The first is the ratio of advertising expenditures reported in Compustat. These data contain not only advertising expenditures spent for media relations but also other advertising activities such as promotion of products through product fairs. The second measure I use comes from a media expenditure tracking company, TNS Media Intelligence, and it spans 2002 to 2006. I consider this second measure a better measure of "mass media" related advertising expenditures. TNS Media Intelligence gathers the data by continually monitoring multiple media channels and collecting information about observed advertisements. The database reports media spending by brand. The media channels include several media outlets such as newspapers, network television, and cable television

[5] Indirect holdings refer to holdings of those that related (such as spouse, child) as well as entities such as trusts. Results are robust to excluding indirect holdings.

(Appendix I provides a comprehensive list of these media channels). I aggregate the advertising outlays of all brands that belong to a particular sample firm for a calendar year to calculate annual advertising spending of a firm. I use the SOUNDEX algorithm of SAS to match firm identifiers in CRSP. After generating a list of potential matches to the name, I hand-match the names to the corresponding Permno number (CRSP identifier) by inspecting the firm's name using a conservative approach: names for which I cannot identify a unique match are excluded from the sample. As a result, from a total of 9,604 firm names that exist in CRSP over the sample period, the matching procedure matched 1,457 unique firm names in the Media Intelligence database.

III. Results and Discussion

III.1 Summary Statistics

Table III presents summary statistics for the panel data used in this paper. The sample contains 7,531 firms, where a firm is defined as an entity with a unique CRSP Permno identifier, and spans eleven years (1995–2006). The average number of firms in a given year is 3,244. The *All Coverage* variable in Table III reports the number of times in a given year that newspapers (*Wall Street Journal* and *New York Times*) and newswire (Dow Jones) report a story on a firm. On average, a typical firm was covered around 15.5 times per year in Dow Jones, *Wall Street Journal*, and *New York Times*. Dow Jones coverage constitutes a major component of media coverage variable. Taking it out lowers the average (median) media coverage to 2.74 (0.00). The average media coverage per year peaks at 20 around the year 2000—i.e., the time of the tech bubble. Compared with the universe of COMPUSTAT firms for the same time period, 1995–2006, my sample contains larger firms. The pooled average market value of equity in sample is $2.9 billion, with a median of $263 million, whereas the pooled average of market value of equity in COMPUSTAT is $1.3 billion, with a median of

$76 million. The Tobin's Q of the sample has a mean of 4.17 and median of 2.15. This ratio is larger than that of the universe of COMPUSTAT firms for the same time period, 3.02 (mean) and 1.52 (median). The average annual advertising expenses to total assets as reported in COMPUSTAT (data item 45) for the sample firms is about 1.1%, with a median of 0%. This figure corresponds to annual advertising spending of $66 million. Average spending on related advertising outlays tracked by the TNS Media Intelligence database was $9.464 million annually.[6]

The average number of analysts following the firm's stock is 3.28, which is statistically lower from the average analyst following of First Call database's number of estimates data (3.48) for the corresponding time period. Average institutional ownership during the sample period (33.8%) is greater than the average percentage of institutional ownership reported by Thompson 13F filings (29.5%). The binary variable that measures the link to mass media, *MediaLink*, takes a value of 1 for 130 companies in a typical year. The ratio of companies with a media expert on board increased from 2.04% to 3.88% over the course of the sample period. A total of 417 companies had a media expert at the firm at some point during the sample period, which corresponds to 1,591 firm-year observations in the sample.

In Panel B of Table III, I examine differences in characteristics of firms with a media expert and firms without a media expert. I report difference of means tests for each pair, with p-values computed using standard errors adjusted for clustering by firm. These tests indicate that firms with a media expert are covered more than firms without a media expert. After all, as the results in Panel B of Table III show, firms with media experts also have larger market capitalization and spend more on advertising at national newspapers. Furthermore, firms

[6] If a firm does not report advertising expenditures for a given year, I assume advertising expenditure is 0 for that year. Similarly, if a company does not have any coverage in TNSMI, I impute 0 to those years. The results are not sensitive these assumptions.

with media experts are covered by more analysts (7.26 vs. 2.69) and have more institutional ownership (52% vs. 33%).

<Insert Table III here>

III.2 Which Firms Hire Media Experts?

Not all companies are likely to need a media expert. In this section, I investigate what determines the existence of newspaper media expertise in a firm. In Table IV, I estimate the following specification using Probit to investigate the determinants of Media Link:

$$\textit{Media Link} = \text{a} + \text{b}*\textit{Controls} + \text{c}*\textit{Fixed Effects} + \text{residual}.$$

Consistent with the univariate analysis presented in Table III, firms that are more visible (i.e., have higher market capitalization) are likely to have media experts on board. One standard deviation increase in firm size increases the probability of employing a media expert by 1.88%. The effect of market capitalization is large compared with the unconditional probability of having a media expert (1.20%).

<Insert Table IV here>

Consistent with the argument that media expertise may help firms manage their media related expenses effectively, I find that firms with more advertising expenditures (measured by log of dollars spent on advertising expenses) are more likely to have media experts on board. A one-standard-deviation increase in log advertising expenditure (2.98) corresponds to a 0.24% increase in the probability of having a media expert on board. The existence of a media expert is positively correlated with prior returns and negatively correlated with current accounting performance, as measured by industry-adjusted return on assets (*ROA*) and share turnover.[7] A one-standard-deviation increase in firm performance corresponds to a decrease in the probability of media on board by 0.31%, whereas a one-standard-deviation increase in prior stock return performance and share turnover is associated with a 0.20% and a –0.44% increase in media on board probability, respectively. In this multivariate setting, institutional ownership and analyst following have no statistical significance when firm size is included in the specification.[8]

III.3 Benefits of Media Experts

What Determines News in the Press?

In this section, I investigate the determinants of media coverage and how future media coverage changes with the existence of media experts on board (*MediaLink*). The dependent variable in this analysis is one-year-ahead media coverage, where media coverage is measured by the natural logarithm of 1 plus the number of articles that appeared in *Wall Street Journal*, *New York Times,* and *Dow Jones* over the course of a calendar year.

The list of determinants of media coverage includes the following: industry dummies, prior year media coverage, firm market capitalization, firm growth, prior return, share turnover, institutional ownership, analyst coverage, and advertising-related variables (*Ad&promotion%* and *advertising expense*). Most of these variables have been shown to be associated with media coverage by Dyck, Volchkova, and Zingales (2008), Feng and Peress (2009) and Gurun and Butler (2009).

If journalists are catering stories to the tastes of readers, it is possible that certain industries (e.g., the motion picture industry) will get more coverage than the others (i.e.,

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[7] I use industry adjusted *ROA* throughout the paper, where industry is defined by 48 Fama-French industry classification (Fama and French (1997). My results are not affected if I use unadjusted *ROA*, or different Fama-French industry classification (24 or 36).

[8] In untabulated analysis, I created a single factor to capture the common variation in firm size, institutional ownership and analyst following to capture firm visibility using different and included this factor in the specification. My conclusions are unaffected by such alternative econometric specifications.

mining). I include industry dummy variables to capture such industry-specific variation in media coverage.[9] Similarly, larger companies and companies that are growing are also more likely to attract media attention if these companies are more likely to owned by many individual investors. Miller (2006) finds that the media are more likely to fill a watchdog role for firms with a larger public following, for a richer information environment, and where the story is more likely to be sensational and interesting to the public. I include firm market capitalization (measured by log of market value of equity) and growth rate (measured by market-to-book ratio) to capture these dimensions.

If bad news is more likely to be of interest to media, then certain market participants, such as institutional owners and sell side analysts, may influence what media writes about companies. I use percentage of a firm owned by institutions to capture institutional activism that is likely to reveal newsworthy stories to media. Likewise, compared with individual investors, analysts are more likely to uncover "sensational" stories that are more likely to appear in newspapers. I include institutional ownership percentage and analyst following to capture "mediating" roles of institutional owners and sell side analysts to uncover "bad news."

Lou (2009) presents evidence that managers adjust firm advertising expenditures prior to important events such as seasoned equity offering and insider sales.[10] Gurun and Butler (2009) argue that advertising expenditures play a "quid pro quo" role in firm-media relations—i.e., firms spending more for local newspaper advertising get a favorable slant from local newspapers; however, such a relation does not exist for national newspapers. I

[9] I obtain similar results when I use an industry classification which uses an end consumer point of view (e.g. "consumer industries" vs. "non-consumer industries").
[10] Chemmanur and Yan (2008) document patterns consistent with manipulation of advertising expenditures around intial public offerings.

include advertising expenditures in my analysis to capture the influence of advertising expenditures on media coverage.

Dyck, Volchkova, and Zingales (2008) argue that inclusion of media coverage in past years is a good proxy that can capture the different levels of "newsworthiness" of different companies. Therefore, I include a lag media coverage variable to capture newsworthiness using the following equation:

Future Media Coverage = a + b1**Media Link*+ b2**ROA* + b3* *Media Link x ROA* +c**Controls* + d**Fixed Effects* + residual

I include industry fixed effects (or, as in one specification, firm fixed effects), year dummies, and an intercept tem. Because the left-hand-side variable is one-year-ahead coverage, media coverage data spans 1995 to 2007, whereas independent variables are measured using observations from 1995 to 2006. The first specification reports the answer to main question of this paper when none of the control variables discussed above are included in the specification. For main tests I have 36,792 firm-year observations if TNS Media Intelligence advertising expense data are not used. The sample size reduces to 13,902 if TNS Media Intelligence data are used in the specification. I compute heteroskedasticity-robust standard errors adjusted for clustering by firm. Table V presents the results of several regression specifications.

<Insert Table V here>

The first specification uses a measure of firm performance, industry-adjusted ROA, a binary variable to measure media expertise in a firm (*MediaLink*), and an interaction of these two terms (*MediaLinkxROA*). If media experts are conveying good news and suppressing bad news, then we expect *MediaLinkxROA* to be positive. The asymmetry in what is reported in the media is an indication that existence of media experts is a useful predictor of future coverage.

Consistent with the argument that media expertise increases the media coverage, I find the coefficient of *MediaLink* to be positive and significant. Since the dependent variables are in logarithms, the coefficients can be interpreted as percentages. In specification I, results indicate that having a media expert on board increases the media coverage by 83.5%.

In the second specification, including the past coverage to capture average newsworthiness of the firm increases the R^2 from 0.23 to 0.65 and reduces the coefficient of *MediaLink* to 0.259. This corresponds to 25.9% more articles per year.

As discussed before, *MediaLink* is correlated with several factors that can also be correlated with media coverage. In the third specification I include several variables that the literature has suggested to explain media coverage. In this specification, the coefficient of *MediaLink* is still economically (10.2%) and statistically significant and the coefficient of the interaction term between *MediaLink* and *ROA* (*MediaLinkxROA*) is positive and significant.

In fourth specification, I reestimate the third specification after *excluding* years when media experts are on the boards of firms from the analysis. The purpose of this analysis is as follows: If firms know that a particularly negative (or positive) publicity event is coming up, they will be more likely to seek advice from a media expert or a public relations firm. That is, the association between asymmetric media coverage and the existence of media experts may be driven by contemporaneous events occurring in the years that media experts are hired. Investigating the relation between asymmetric media coverage and existence of media experts *after* the hiring year mitigates the contemporaneous event effect to the extent that the contemporaneous event does not repeat in the years following hiring of media experts. I find that the relationship between asymmetric media coverage and existence of media experts *does not attenuate* when I exclude the years media experts are on the boards of firms from the analysis.

In the fifth specification, in which I include a direct measure of mass media related advertising expenses, I find that the coefficient of *ROA* for a firm with a media expert is 0.481 (0.606–0.125). One standard deviation in *ROA* (0.20) corresponds to a 0.10 unit increase in log coverage. This corresponds to approximately 10% higher coverage when compared with the average coverage of companies without media expertise.

It is possible that unidentified firm characteristics may be related to media coverage. I include firm fixed effects in the regression specification and focus only on the within-firm variations in media coverage. The sixth specification replaces industry dummies with firm fixed effects. If any omitted firm-specific, time-invariant factors drive the results in our first specification, adding firm dummies will capture the impact of these factors. The coefficient estimate on connected ownership decreases by about 80% to 0.023 and lacks statistical significance. This may be an indication that a board member with media expertise has been on board a long time, leading to a low variation in this variable. The interaction term *MediaLinkxROA*, however, does not suffer this problem because *ROA* varies significantly over time. This final specification suggests that the coefficient of *ROA* of firms with a media expert is 0.171 (0.247–0.076). One standard deviation in *ROA* corresponds to 3.5 % higher coverage compared with baseline specification.

In Table V, Panel B, I find similar results when I exclude Dow Jones from the sample and use newspaper coverage only (for brevity I report estimates only for models (3) and (6)).

Connections or Expertise

A plausible question at this point is what to expect from *MediaLink* if it denotes the former editor of, say, *Podunk Herald*. How would this person affect the extra coverage in a nationwide newspaper like *Wall Street Journal*? The *MediaLink* variable not only captures the connections provided by the media person but also values his expertise, including choosing a good public relations firm or investor relations firm (Solomon (2009)). In Panel C of Table V, I restrict the sample to those media experts that had ties to *Wall Street Journal, New York Times,* and *News Corporation,* the owner of the media outlets I am using to measure coverage. I find that the coefficients of both *MediaLink* and *MediaLinkxROA* are economically larger than estimates provided in Panel A of Table V. The increase in the coefficient *MediaLinkxROA* is twofold and fourfold in models (3) and (6), respectively. In others words, this finding suggests that media experts use their *connections* to affect media coverage of *their* connected media outlets, to the extent that media experts from higher-profile media outlets do not have more *expertise* in managing media relations compared with media experts from other media firms.

Nonrandom Assignment of Media Experts Across Firms: Treatment Effects Model

Assume that the need to hire a media expert arises because of stringent labor relations expected in the future or some lawsuit that will lower the prestige of the firm. In such cases, the willingness of media experts to sit on the board will go down; the willingness of firms to hire a media expert, however, will go up. Econometrically this corresponds to a negative correlation between the error terms of the media coverage model and the media expert model, which leads to a downward bias in the OLS estimate.

The reason why this can happen is simply because media experts are not randomly distributed to firms. Firms choose to hire media experts, and the need to hire media experts may be unobservable. Furthermore, the unobservable need to hire media experts may also be correlated with future media coverage.

In Table VI, I use a treatment effects model to incorporate the endogenous nature of having a media expert. Specifically, my primary regression model estimates the effect of a binary treatment, *MediaLink,* on future media coverage (*future media coverage model*). The binary variable, *MediaLink*, is further modeled endogenously as a function of several factors, including the ones analyzed in Table IV (*media expert model*). I also include prior media coverage, a factor that has been shown to capture newsworthiness, in both equations of the treatment effect model. If the error term in *future media coverage model* and the error term for hiring a *media expert model* are correlated, OLS will be biased. If this correlation is negative (positive), OLS coefficient will be biased downward (upward).

First two columns in Table VI report the results of the treatment effects model for the full sample. It is important to note that in the full model, I exclude the interaction term that involves the endogenous variable (*MediaLinkxROA*) because the treatment effects model considers endogeneity effects only in one variable. As noted in Wooldridge (2002, p. 236), simply including an interaction term would produce inconsistent estimates. I estimate the treatment effects model using a maximum likelihood. The results in Table VI show that the coefficient of *MediaLink* is positive and significant at the 1% level, consistent with the finding reported in Table V. More important, correlation between the errors of the treatment effects model's first-stage and second-stage residuals is negative (*rho* = –0.276), and the magnitude of this coefficient is 4.3 larger than the OLS coefficient of the model that incorporates all control variables (third column) in Table V.

Because I exclude the interaction term that involves the endogenous variable (*MediaLinkxROA*), as treatment effects model considers endogeneity effects only in one variable, I estimate the model over two subsamples to recapture the flavor of the interaction term by splitting the sample in two by using median *ROA* as the cutoff value. In the third and fourth columns of Table VI, results show that in firms with high *ROA* (*ROA* higher than sample median *ROA*), the coefficient of *MediaLink* is statistically and economically higher than that of firms with low *ROA* ($p = 0.00$). This finding suggests that, compared with media experts on boards of firms performing poorly (lower *ROA*), media experts on boards of firms performing well (higher *ROA*) get higher media coverage.

<Insert Table VI here>

Model Misspecification and Propensity Score Matching

Results obtained from the treatment effects model support the notion that existence of media experts is not due to selection bias. Another technique, propensity score matching, is often used in the literature to investigate the "treatment effects." The propensity score method forms matched pairs of firm-years with similar need for media exposure but different realizations of hiring media experts. The main benefit of this approach is to mitigate model misspecification—i.e., an incorrect functional form for the relation between the variables of interest (*MediaLink* and control variables used in column 4 of Table V) and the outcome (future media coverage). Table VII reports the average treatment effect (ATE) of having a media expert on board. To implement the matching estimator, I use kernel weighting with the normal kernel and a fixed bandwidth of 0.10. Confidence intervals are obtained using 500 bootstrap repetitions. The magnitude of this estimate, 0.221, is half the size of what I found using the treatment effects model.

Next, I use the bounding techniques of Rosenbaum (2002) to evaluate the sensitivity of my results to "hidden bias," or unobserved correlated omitted variables. This bounding approach provides insight into the likelihood that my results are confounded by such explanations as endogenous matching of media experts and media coverage on the basis of unobserved variables, such as the unobserved newsworthiness of the firm.

<Insert Table VII here>

Rosenbaum (2002) shows that hidden bias exists if two observations have the same observed covariates but have different probabilities of receiving treatment because of some unobserved factor. If two observations look similar across their observable covariates, a matching algorithm to mitigate overt bias would pair them. If odds ratio (Γ) is equal to 1, as it would be in a randomized experiment, the model is said to be free of hidden bias. In this case, controlling for selection on observables would yield an unbiased estimate of the treatment effect.

If the odds ratio (Γ) is not equal to one, each observation in a matched pair has an unequal probability of receiving treatment, which leads to a hidden bias. Higher value of Γ means that unobservables have an effect in the treatment selection process. For example, Γ = 2 implies that observationally identical firms differ in their relative odds of treatment by a factor of two. Rosenbaum (2002) shows that relaxing the assumption that Γ = 1 (i.e., that two observations with identical observable covariates have an identical probability of receiving treatment) can be used to compute significance test boundaries under different assumptions about the strength of the hidden bias that is necessary to alter the qualitative inferences from a study.

I summarize Rosenbaum bounds obtained for varying odds ratios (Γ) in Table VII. Under a small amount of selection on unobservable (Γ=1.3) we reject the null that the ATE is zero. In other words, observationally identical firms should differ in their relative odds of treatment by a factor of roughly 1.3 to turn the results around. Therefore, Rosenbaum bounds results provide comfort for the robustness of the ATE estimate.

III.4 Cost of Hiring Media Experts: Liquidity Discount

The result that firms with good (bad) news that have a media expert on board is covered more (less) than a set of control firms should have implications for prices if some investors believe that media experts distort their information set and create information asymmetry among investors.

Kelly and Ljungqvist (2009) show that an increase in information asymmetry among investors leads to a reduction in uninformed investors' demand for the risky asset and thus lowers prices. Using the framework of Grossman and Stiglitz (1980), they show that the factor that links information asymmetry to price is liquidity risk. They further test their prediction using terminations of analyst coverage as an exogenous shock to information asymmetry. I employ their research design to test whether exposure to liquidity risk before and after hiring a media expert is different. My main purpose is to see if distortion of information set via media coverage manipulation is related to an increase in liquidity risk.

I use the following model proposed by Kelly and Ljungqvist (2009):

$$r^{e}_{i,t} == \alpha_i + (\beta_i + \Delta\beta_i^{Post} I_{t\epsilon Post} + \Delta\beta_i^{Post\&MediaExpert} I_{t\epsilon Post} I_{i\epsilon MediaExpert}) \, Factors_t + \epsilon_{i,t}$$

where $r^{e}_{i,t}$ is stock *i*'s month-*t* return in excess of the risk-free rate. $I_{t\epsilon Post}$ is an indicator for the post-event period, where event refers to calendar year of and years after hiring the media expert. $I_{t\epsilon MediaExpert}$ is an indicator to identify firms with media experts. *Factors* is a vector that includes the three Fama-French factors (*MKT*, *SMB*, and *HML*) and liquidity factor (*LIQ)*. I use *LIQ* to proxy for liquidity risk. Table VIII reports results for three alternative versions of *LIQ*: Pastor and Stambaugh's (2003) nontraded liquidity factor (Panel A.1), Pastor and Stambaugh's (2003) traded liquidity factor (Panel A.2), and Sadka's (2006) permanent liquidity factor (Panel A.3).[11]

<Insert Table VIII here>

I use the methodology of Daniel and Titman (1997) to obtain characteristic-matched

[11] Kelly and Ljungqvist (2009) do not use momentum factor in their tests, arguing that momentum factor is largely driven by liquidity (see Sadka, 2006). I also exclude momentum factor from the tests. Including momentum to all tests does not change my results and conclusions.

control firms. Characteristics used to match stocks are their market capitalization, book-to-market ratio, and momentum. Market capitalization is taken as the value in the previous December. The book-to-market ratio is the ratio of the Compustat book value of equity to market value of equity, where the values used in December of year *t–1* are matched to stock returns from July of year *t* to June of year *t+1*. Momentum is the cumulative stock return from 12 months ago to 2 months ago, inclusive. Stocks are split into quintiles of these values based on breakpoints of all NYSE stocks for the month in question.

This specification allows me to measure whether a stock's factor loadings change after hiring a media expert, compared with otherwise similar control firms that have no media expert. This effect is captured by the difference-in-differences term, $\Delta\beta_i^{Post\&MediaExpert}$.

I estimate the model with monthly data. Following the estimation procedure outlined in Kelly and Ljungqvist (2009) and Pastor and Stambaugh (2003), I impose a restriction on $\Delta\beta_i^{Post}$ and $\Delta\beta_i^{Post\&MediaExpert}$: that these coefficients are common to all firms. Specifically, for each firm in the treatment and control group, I concatenate the pre- and post-event returns and stack all firms data in a single panel. In step 1, I estimate the above model firm by firm using OLS and construct residuals: $n_{i,t} == r^e_{i,t} - (\alpha_i + \beta_i\ Factors_t)$. I use these residuals as dependent variables in a second step, pooled regression, $n_{i,t} == \alpha_i + (\Delta\beta_i^{Post}\ I_{t\epsilon Post} + \Delta\beta_i^{Post\&MediaExpert}\ I_{t\epsilon Post}\ I_{i\epsilon MediaExpert})\ Factors_t + \epsilon_{i,t}$. I exclude sample firms when control firms do not have sufficient data.

In each specification reported in Table VIII, the liquidity coefficient estimate for $\Delta\beta_i^{Post\&MediaExpert}$ is positive and statistically significant. These results suggest that the returns of companies hiring media experts become more sensitive to liquidity risk, relative to matched firms with no media experts. Using a one-standard-deviation change in liquidity factor returns in my sample period and the coefficient estimates for $\Delta\beta_i^{Post\&MediaExpert}$ reported in Panels A.1, A.2, and A.3, I find that expected returns increase by between 25, 23, and 10 basis points/month, respectively, following appointment of a board member with media expertise. These monthly discounts correspond to 1.2% to 3.0% in liquidity discounts per year.

In order to isolate liquidity premium affects of contemporaneous events in the year a media expert is hired, I replicated the analysis by focusing on the liquidity premium year *after* media expert is hired and found similar results.

Changes in loadings on the *SMB* are statistically zero. Statistical significance of the change in loadings on the *Market* is model specific. Changes in loadings on *HML,* however, are negative and statistically significant, indicating that firms with media experts have lower exposure to risks proxied by *HML*. A one-standard-deviation increase in *HML* (3.32%) corresponds to a reduction of 20 to 25 basis points per month in expected returns, an amount close to the expected return increase due to the illiquidity premium. One possible explanation for reduction in exposure to *HML* is increase in the market value of the firm due to the intangible benefits of advertising. If firms hiring media experts create value through finding efficient means of advertising, then market value of firms would reflect such value-enhancing activities. Because advertising is expensed and not capitalized, its value is not reflected on the balance sheet in a timely manner. Therefore, reduction to exposure to *HML* risk may simply reflect the increase in intangibles due to advertising. This explanation is consistent with the arguments articulated in Daniel and Titman (2004), who argue that *HML* does not proxy for bankruptcy risk but captures risks associated with intangibles. Daniel and Titman (2004) argue that stock returns are strongly negatively related to "intangible" returns—i.e., the book-to-market ratio forecasts returns, because they proxy for the intangible return.

Causality: Insider Ownership as Instrumental Variable for Media Coverage

In order to isolate liquidity premium affects of contemporaneous events in the year a media expert is hired, I replicated the analysis reported in Table VIII by focusing on the liquidity premium year *after* the media expert is hired and found similar results (Table VII, Panel B). Although this finding provides some comfort in the robustness of the positive correlation between existence media experts on board and illiquidity, they say nothing about causality. This is simply because the choice to hire media experts could be endogenous to the cost of capital and media coverage needs. That is, it is possible that firms are more likely to seek media experts in years they have information asymmetry–increasing events, such as reduction in voluntary disclosure by managers. This can happen for a couple of reasons. For example, if journalists rely on voluntary disclosure of managers to report on these firms, then reduced voluntary disclosure (e.g., information asymmetry–increasing events) would reduce coverage by newspapers regardless of any effort by media experts.

To attempt to disentangle direct effects (media expert–caused coverage) and indirect effects (e.g., journalists' efforts to report on firms) on illiquidity, I instrument press coverage (*All Coverage*) with the *media experts' ownership* of the corresponding firm. *Illiquidity* in this analysis is measured by the average of Amihud's (2002) illiquidity measure over the following calendar year.

I expect the media experts to lobby the press if they have some skin in the game; therefore, *media experts' ownership* can be considered a good measure of the exogenous component in news coverage. In their paper, Dyck, Volchkova, and Zingales (2008) use a very similar approach when they investigate the causality between a hedge fund's holdings and its motivation to leak stories to international media like *Financial Times*. In that sense, my research design as well as the construction of my instruments mimics their approach.

My instrument, *media experts' ownership,* is strongly related to *All Coverage*: the *F*-statistics on the instruments in the first stage is well above critical values from a Stock-Yogo weak identification test. The *F*-statistic for the *media experts' ownership* equation is 87. Further, the first-stage R^2 is large, 0.85, indicating that my estimation is efficient. Because it seems unlikely that media experts' holdings induce future illiquidity for a particular firm, it seems likely that my instruments meet exclusion requirements. In the last column of Table IX, I report the first-stage regression estimates. The results suggest that *media experts' ownership* is correlated with *All Coverage*. I report the second-stage results of the instrumental variables regression in the first column of Table IX.

Consistent with the hypothesis that a media expert on board causes future illiquidity, I find that the coefficient on the instrumented *All Coverage* variable is statistically significant, with an estimated coefficient of 8.014. A one-standard-deviation increase in *All Coverage* corresponds to 7.75, about 50% of a one-standard-deviation increase, in the Amihud illiquidity measure.

This result means that, to the extent that my instrumenting strategy successfully captures the exogenous portion of media coverage, media experts *cause* an increase in future illiquidity. Furthermore, because my sample includes the names of board members with media expertise that I matched to insider files, my sample selection procedure excludes media experts without any ownership in firms that they sit on the boards of. This introduces a measurement error in the *media experts' ownership* variable and reduces the power to detect a relationship between illiquidity and press coverage.

<Insert Table IX here>

IV. Conclusion

The unique contribution of my paper is to show that certain individuals that sit on boards of corporations influence the media exposure of their firms. Existence of board members who have mass media experience at an owner/editor/journalist level predicts future press coverage. The most conservative estimates show that media coverage increases by more than 20% after hiring media experts. In good (bad) times, the firms with a media expert on board are covered more (less) than a set of control firms.

The result that firms with good (bad) news that have a media expert on board is covered more (less) than a set of control firms has implications for prices as it distorts the information set of investors who rely on media as an information source. I show that one of the channels in which this distortion reveals itself is liquidity. Firms with media experts suffer up to 3% per year in discount rate due to illiquidity. By using the *ownership* of media experts as an instrument to engage in lobbying activities, I find that the relation between the existence of media experts on board and future illiquidity is causal: media experts cause illiquidity to increase.

My study complements recent finding of Cohen, Frazzini, and Malloy (2009) that connections matter in independent board member selection. Findings in my and their study suggest that both practitioners and researchers should be cautious in their expectations from so-called independent board members.

My results also have implications for standard setters attempting to increase participation in financial markets. If the media, the most widely available information source of uninformed investors, slant information in predictable ways, would it make sense to regulate relations between media and firms? I believe not. In my setting, a media expert is essentially a proxy for media-linked ownership. To the extent that media-linked ownership acts like media expert ownership, perhaps what needs to be closely monitored is the ownership of media companies in other companies.

Appendix I. Various Media Outlets from Which the Advertising Data Are Collected

TNS Media Intelligence (TNSMI) provides advertising expenditures at the brand level (as defined by TNSMI) across eleven advertising categories listed below from 2002 to 2006.

1. Network TV: The Network TV service provides expenditure information for seven broadcast networks, ABC, CBS , FOX , NBC , PAX/I, MNTV, and CW.

2. Cable TV: The Cable TV Service provides expenditure information for 52 cable television networks.

3. Syndication TV: The Syndication TV service provides expenditure information for major local markets. Syndication advertising scope is somewhere in between the Network TV and Spot TV.

4. Spot TV: Spot TV service provides expenditure information for major local markets.

5. Magazine: This service measures and compiles all expenditure data for Publishers Information Bureau, Inc. (PIB). Publications measured must be members of PIB, and currently include 350+ consumer magazines.

6. Sunday Magazines: Sunday Magazines service measures five PIB Sunday magazines: *New York Times Magazine*, *Los Angeles Times Magazine*, *Life Magazine*, *Parade*, and *USA Weekend*.

7. National Newspapers: This service measures advertising in three national newspapers: *New York Times*, *USA Today,* and *Wall Street Journal*.

8. Newspapers: Newspaper service measures advertising in over 250 daily and Sunday newspaper editions and Sunday magazines.

9. Network Radio: Network radio includes the following networks: ABC, American Urban, Premier, and Westwood.

10. National Spot Radio: National spot radio service provides nationally placed spot radio data for approximately 4,000 stations in major local markets.

11. Outdoor Advertising: Outdoor advertising service reports billboard expenditures in major local markets in the United States.

Appendix II. Variable Definitions

Connections Variable:

MediaLink: Dummy variable that takes a value of 1 if a firm in a given year has an insider (media expert) with prior or contemporaneous media experience.

Coverage Variables:

All Coverage (raw): Number of times in a given calendar year *Wall Street Journal, New York Times,* and *Dow Jones* report a story on a firm.

Newspaper Coverage (raw): Number of times in a given calendar year *Wall Street Journal* and *New York Times* report a story on a firm.

All Coverage: Ln (1+All Coverage(raw)).

Newspaper Coverage: Ln (1+ Newspaper Coverage (raw)).

Advertising Variables:

Ad&Promotion%: This item represents the cost of advertising media (radio, television, newspapers, periodicals) and promotional expense (Compustat data item 45) divided by total assets.

Advertising Expense: Advertising figure provided by TNS Media Intelligence for the items summarized in Appendix I. (Source: TNS Media Intelligence).

Other Variables:

Total Assets: Compustat annual data item 6. This item represents current assets plus property, plant, and equipment, plus other non-current assets (including intangible assets, deferred charges, and investments and advances).

Market Value of Equity: Measured at the end of the fiscal year using the multiplication of CRSP-Compustat data item 25 and data item 24.

Book Value of Equity: Measured at the end of the fiscal year CRSP-Compustat data item 60.

Prior Return: Cumulative 12-month raw return. (Source: CRSP monthly stock file.)

Analyst Following: Number of analysts following a firm at the end of prior calendar year's (Source: First Call database.)

% of Institutional Ownership: Number of shares owned by institutional investors reporting 13F divided by total number of outstanding shares at the end of prior calendar year. (Source: Thomson Financial Institutional 13F Files.)

Turnover: Average monthly turnover ratio in a calendar year (Vol/Shrout). (Source: CRSP monthly stock file.)

ROA: Fama and French (1997) 48 industry adjusted Return on Assets (data item 13 / data item 6). (Source: CRSP-Compustat Merged File).

Media Experts' Ownership: Natural logarithm of 1 + dollar amount of ownership of media experts in firm (Source: Thomson Financial Institutional Insider Ownership Files.)

Illiquidity: Amihud illiquidity measure, average over year of $10^6 \times$ abs(ret)/(abs(prc) $\times$ vol).

Table I. Sample Collection - List of Newspaper Publishing Companies and Flagship Newspapers

	Company	Flagship Newspapers		Newspaper Network
1	New York Times Co.	New York Times	Boston Globe	17 newspapers in 8 states
2	Gannett Company, Inc.	USA TODAY	Arizona Republic	91 newspapers in 35 states
3	News Corporation	Wall Street Journal	New York Post	7 newspapers in 3 states
4	Tribune Company	Los Angeles Times	Chicago Tribune	15 newspapers in 8 states
5	Knight Ridder	Detroit Free Press	Kansas City Star	32 newspapers in 10 states
6	Lee Enterprises, Inc.	St. Louis Post-Dispatch	Arizona Daily Star	51 newspapers in 22 states
7	E.W. Scripts	Rocky Mountain News	Knoxville News Sentinel	19 newspapers in 11 states
8	The McClatchy Company	Miami Herald	Fort Worth Star-Telegram	32 newspapers in 16 states
9	Hearst Newspapers	San Francisco Chronicle	Houston Chronicle	12 newspapers in 6 states
10	Washington Post	Washington Post	The Herald (Everett)	8 newspaper in 2 states
11	MediaNews Group, Inc.	San Jose Mercury News	Detroit News	53 newspapers in 14 states
12	Journal Registry	Oakland Press		22 newspapers in 7 states
13	Seattle Times	Seattle Times		1 newspaper in 1 state

Table II. Media Experts by Publishing Firm

In this table, the column titled "Media Expert" reports the number of individuals that worked at the corresponding publishing firm. The column titled "Matched to Insider Files" reports the number of individuals that not only worked at a publishing firm but also had insider ownership at a public firm between 1995 and 2006.

	Company	Media Expert	Matched to Insider Files
1	New York Times Co.	230	95
2	Gannett Company, Inc.	189	85
3	News Corporation	182	75
4	Tribune Company	118	68
5	Knight Ridder	94	57
6	Lee Enterprises, Inc.	92	41
7	E. W. Scripts	91	56
8	The McClatchy Company	82	36
9	Hearst Newspapers	68	33
10	Washington Post	54	35
11	MediaNews Group, Inc.	44	14
12	Journal Registry	31	25
13	Seattle Times	9	6
		1,284	626

Table III. Descriptive Statistics of Variables

Panel A of this table summarizes the characteristics of the firms analyzed in the paper. Panel B provides univariate statistics of firm-year observations with and without a media expert. Comparison of mean values as well as firm-level clustered *p*-values are provided in the last column of Panel B. The sample period is 1995–2006 and unit of observation is firm-year. Descriptions of variables are provided in Appendix II.

Panel A. Descriptive Statistics

	All Coverage (raw)	*Newspaper Coverage (raw)*	*MediaLink*	*Ad&Promotion %*
Mean	15.514	2.740	0.029	0.011
Median	9.000	0.000	0.000	0.000
Std. Dev.	35.642	10.968	0.168	0.048
P5	1.000	0.000	0.000	0.000
P95	42.000	11.000	0.000	0.057
N	36,762	36,762	36,762	36,762

	Market Value of Equity	*Market/Book*	*Advertising Expense*	*Institutional Ownership %*
Mean	2,972	4.171	9,464	0.368
Median	263	2.150	0	0.333
Std. Dev.	15,756	22.308	85,202	0.305
P5	12	0.655	0	0.000
P95	10,213	10.809	21,469	0.886
N	36,762	36,762	13,902	36,762

	Amihud Illiquidity	*Prior Return*	*Turnover*	*Analyst Coverage*	*Industry Adjusted ROA*
Mean	2.769	0.177	1.464	3.289	0.011
Median	0.071	0.047	0.930	1.000	0.017
Std. Dev.	15.600	0.978	1.872	4.802	0.192
P5	0.003	-0.715	0.141	0.000	-0.322
P95	11.300	1.348	4.422	14.000	0.263
N	36,762	36,762	36,762	36,762	36,762

Panel B. Comparison of Means of Samples with/without *Media Experts*

	Without *Media Expert*	With *Media Expert*	*p*-value
All Coverage	13.71	41.09	0.000
Newspaper Coverage	2.19	14.61	0.000
Ad&Promotion %	0.010	0.014	0.897
Prior Return	0.163	0.162	0.978
Turnover	1.340	1.392	0.274
Market Value	1870	19,395	0.000
Market/Book	4.016	4.186	0.946
Advertising Expense	3,915	82,927	0.000
Institutional Ownership %	0.33	0.52	0.000
Analyst Coverage	2.69	7.26	0.000

Table IV. Determinants of *MediaLink*

This table reports the results of the following pooled OLS regression: *MediaLink* = a + b**Controls* + c**Fixed Effects* + residual. Unit of analysis is firm-calendar year. The left-hand-side variable, *MediaLink,* is a dummy variable that takes a value of 1 if a firm in a given year has an insider with prior or contemporaneous media experience. The regressors are defined in Appendix II. Heteroskedasticity-robust standard errors are clustered by firm and provided in parenthesis. (***), (**), and (*) represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	MediaLink	*MediaLink*	*Marginal Prob.(x100)*
Ln (Market/Book)	-0.058*	0.045	0.143
	(0.035)	(0.045)	
Ln (MarketValue)	0.308***	0.301***	0.952
	(0.016)	(0.027)	
Prior Return	0.060***	0.079***	0.249
	(0.009)	(0.019)	
Turnover	-0.053***	-0.066***	-0.210
	(0.018)	(0.025)	
ROA	-0.457***	-0.563***	-1.779
	(0.157)	(0.190)	
Ad&Promotion %		0.439	1.386
		(0.564)	
Institutional Ownership %		0.082	0.258
		(0.127)	
Analyst Coverage		-0.004	-0.012
		(0.005)	
Ln (Advertising Expense)		0.025**	0.080
		(0.010)	
Industry FE	Included	Included	
Year FE + Intercept	Included	Included	
Predicted Probability at x-bar			1.21
N	53,356	20,525	
Pseudo R^2	0.23	0.25	

Table V. Determinants of Future Coverage

Panel A of this table reports the results of the following pooled OLS regression: *All Coverage* = a + b1**Media Link*+ b2**ROA* + b3* *Media Link x ROA* +c**Controls* + d**Fixed Effects* + residual. Unit of analysis is firm-year. The left-hand variable, *All Coverage*, is the combined media coverage by *Dow Jones, Wall Street Journal,* and *New York Times*. Panel B reports the estimates of a similar specification by replacing the left-hand variable with *Newspaper Coverage* (i.e., media coverage of *Wall Street Journal* and *New York Times*). The regressors are defined in Appendix II. Heteroskedasticity-robust standard errors are clustered by firm and provided in parentheses. (***), (**), and (*) represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Determinants of coverage by *Dow Jones, the New York Times* and *the Wall Street Journal*

	(1)	(2)	(3)	(4)	(5)	(6)
MediaLink	0.835***	0.259***	0.102***	0.124***	0.109***	0.023
	(0.081)	(0.029)	(0.026)	(0.029)	(0.032)	(0.026)
ROA	0.383***	0.170***	-0.093***	-0.082***	-0.125***	-0.076***
	(0.036)	(0.015)	(0.017)	(0.019)	(0.028)	(0.027)
MediaLink × ROA	1.181***	0.561***	0.460***	0.441***	0.606***	0.247*
	(0.421)	(0.146)	(0.136)	(0.141)	(0.175)	(0.154)
Lag (All Coverage)		0.717***	0.603***	0.604***	0.582***	0.279***
		(0.006)	(0.007)	(0.008)	(0.010)	(0.005)
Ln (MarketValue)			0.114***	0.122***	0.105***	0.111***
			(0.004)	(0.005)	(0.006)	(0.007)
Ln (Market/Book)			0.002	-0.018***	-0.007	0.013**
			(0.005)	(0.005)	(0.007)	(0.006)
Prior Return			0.028***	0.031***	0.015**	0.022***
			(0.004)	(0.004)	(0.007)	(0.003)
Turnover			0.034***	0.030***	0.028***	0.043***
			(0.003)	(0.003)	(0.004)	(0.002)
Institutional Ownership %			-0.164***	-0.145***	-0.164***	-0.120***
			(0.016)	(0.018)	(0.022)	(0.023)
Analyst Coverage			0.004***	0.006***	0.005***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)
Ad&Promotion %			0.173**	0.263***	0.028	0.008
			(0.071)	(0.098)	(0.123)	(0.132)
Ln (Advertising Expense)					0.014***	
					(0.002)	
Firm FE	Excluded	Excluded	Excluded	Excluded	Excluded	Included
Industry FE	Included	Included	Included	Included	Subsumed	Subsumed
Year FE + Intercept	Included	Included	Included	Included	Included	Included
N	39,732	38,009	36,762	29,433	13,902	36,762
R^2	0.23	0.65	0.69	0.72	0.71	0.80

Panel B. Determinants of Coverage by *the New York Times* and *the Wall Street Journal*

	(3)	(6)
MediaLink	0.063**	0.015
	(0.026)	(0.037)
ROA	-0.052***	-0.068**
	(0.017)	(0.029)
MediaLink × ROA	0.474***	0.252*
	(0.144)	(0.154)
Lag (All Coverage)	0.578***	0.270***
	(0.007)	(0.009)
Control variables used in Panel A	Included	Included
Firm FE	Excluded	Included
Industry FE	Included	Subsumed
Year FE + Intercept	Included	Included
N	36,762	36,762
R^2	0.66	0.78

Panel C. Determinants of Coverage by Dow Jones*, the New York Times,* and *the Wall Street Journal* when *MediaLink* is Defined by Connections to Owners of These Outlets.

	(3)	(6)
MediaLink	0.107**	-0.025
	(0.054)	(0.053)
ROA	-0.093***	-0.075***
	(0.017)	(0.027)
MediaLinkxROA	0.801***	0.813***
	(0.272)	(0.295)
Lag (All Coverage)	0.604***	0.280***
	(0.007)	(0.005)
Control variables used in Panel A	Included	Included
Firm FE	Excluded	Included
Industry FE	Included	Subsumed
Year FE + Intercept	Included	Included
N	36,762	36,762
R^2	0.68	0.80

Table VI. Treatment Regression

This table reports the results of the treatment effects model using maximum likelihood method. All variables are defined in Appendix II. Heteroskedasticity-robust standard errors are clustered by firm and provided in parentheses. (***), (**), and (*) represent statistical significance at 1%, 5%, and 10% levels, respectively.

	MediaLink	*All Coverage*	*All Coverage*	*All Coverage*
		Full Sample	*ROA > Median ROA*	*ROA <= Median ROA*
MediaLink		0.431***	0.502***	0.259***
		(0.054)	(0.058)	(0.087)
Lag (All Coverage)	0.164***	0.599***	0.621***	0.568***
	(0.035)	(0.007)	(0.009)	(0.010)
ROA	-0.421**	-0.080***	-0.161***	-0.016
	(0.184)	(0.017)	(0.054)	(0.027)
Ln(Market/Book)	-0.030***	0.004	0.004	0.012*
	(0.041)	(0.005)	(0.007)	(0.007)
Ln(MarketValue)	0.26	0.109***	0.110***	0.107***
	(0.021)	(0.004)	(0.005)	(0.005)
PriorReturn	0.058***	0.026***	0.036 ***	0.021***
	(0.010)	(0.004)	(0.005)	(0.005)
Turnover	-0.053**	0.035***	0.028***	0.044***
	(0.021)	(0.003)	(0.004)	(0.005)
Inst. Owner	0.083	-0.157***	-0.143***	-0.162***
	(0.102)	(0.016)	(0.020)	(0.023)
Analyst Coverage	0.001	0.004***	0.004***	0.004***
	(0.004)	(0.001)	(0.001)	(0.002)
Ad&Promotion %	0.522	0.169**	0.218*	0.149**
	(0.365)	(0.070)	(0.124)	(0.078)
Industry FE	Included	Included	Included	Included
Year FE + Intercept	Included	Included	Included	Included
N	36,762	36,762	19,276	17,486
Lambda	-0.149			
Rho	-0.276			
	(0.036)			

Table VII. Propensity Score (Kernel) Matching Estimates and Rosenbaum Bounds

This table reports the average treatment effect (ATE) of the propensity score matching procedure and Rosenbaum bounds for different levels of unobserved selection (Γ). The propensity score method forms matched pairs of firm-years using the determinants reported in Table IV. Matching estimates utilize the Epanechnikov kernel with a fixed bandwidth of 0.10. I use results of 500 bootstrap repetitions to calculate 95% empirical confidence intervals for average treatment effect. These confidence intervals are reported in parenthesis.

	ATE	Γ = 1	Γ = 1.1	Γ = 1.2	Γ = 1.3	Γ = 1.4	Γ = 1.5
Panel I.							
Media Expert	0.156	p = 0.00	p = 0.00	p = 0.00	p = 0.02	p = 1.00	p = 1.00
(Exists vs. Not Exists)	(0.075, 0.368)						

Table VIII. Liquidity Tests

The table reports changes in equity return factor loadings after a media expert is hired. The year media expert is hired is classified in the "post" ("pre") period in Panel A (B). I estimate four-factor models of firms' monthly stock returns in excess of the risk-free rate. The give factors are *MKT* (the excess of the monthly market return over the risk free rate); *SMB* (the difference between the monthly returns of a value-weighted portfolio of small stocks and one of large stocks); *HML* (the difference between the monthly returns of a value-weighted portfolio of high book-to-market stocks and one of low book-to-market stocks); and one of three liquidity-risk factors, *LIQ*: Pastor and Stambaugh's (2003) nontraded liquidity factor (Panel A.1), and Pastor and Stambaugh's traded liquidity factor (Panel A.2) and Sadka's (2006) liquidity factor (Panel A.3). The *MKT*, *SMB*, HML, and Sadka *LIQ* factor series come from WRDS. Pastor and Stambaugh factors were obtained from Stambaugh's website. I report the coefficent of $\Delta\beta_i^{Post\&MediaExpert}$ in the following specification: $r^e_{i,t} == \alpha_i + (\beta_i + \Delta\beta_i^{Post} I_{t\in Post} + \Delta\beta_i^{Post\&MediaExpert} I_{t\in Post} I_{i\in MediaExpert})$ $Factors_t + \epsilon_{i,t}$ The two-stage estimation method is explained in Section III.4.

Panel A. Changes in equity return factor loadings *during and after* the year of hiring a media expert

MKT	SMB	HML	LIQ
1. Pastor and Stambaugh non-traded liquidity factor			
-0.035**	-0.003	-0.069***	0.037***
(0.017)	(0.015)	(0.019)	(0.011)
2. Pastor and Stambaugh traded liquidity factor			
-0.030*	0.007	-0.051***	0.041***
(0.017)	(0.016)	(0.019)	(0.010)
3. Sadka Permanent Liquidity Factor			
-0.025	-0.012	-0.071***	0.263*
(0.016)	(0.017)	(0.020)	(0.157)

Panel B. Changes in equity return factor loadings *after* the year of hiring a media expert

MKT	SMB	HML	LIQ
1. Pastor and Stambaugh non-traded liquidity factor			
-0.033*	-0.036**	-0.069***	0.041***
(0.019)	(0.016)	(0.020)	(0.012)
2. Pastor and Stambaugh traded liquidity factor			
-0.025	-0.027	-0.049**	0.045***
(0.018)	(0.016)	(0.020)	(0.011)
3. Sadka Permanent Liquidity Factor			
-0.025	-0.051***	-0.082***	0.359*
(0.018)	(0.018)	(0.021)	(0.199)

Table IX. Insider Holding of Media on Board and Future Illiquidity

This table reports the results of the first- and second-stage results of the 2SLS regression that uses *Ln(1+Insider Ownership)* to instrument *All Coverage.* I estimate the following: *Future Illiquidity* = a + b1**Coverage*c**Controls* + d**Fixed Effects* + residual. The regressors are defined in Appendix II. Heteroskedasticity-robust standard errors are clustered by firm and provided in parentheses. (***), (**), and (*) represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Illiquidity	All Coverage
All Coverage	8.014***	
	(1.955)	
ROA	2.361**	-0.352***
	(1.037)	(0.036)
Ln(MarketValue)	-3.928***	0.191***
	(0.447)	(0.008)
Ln(Market/Book)	0.339	-0.096***
	(0.264)	(0.010)
PriorReturn	-0.601***	-0.001
	(0.094)	(0.004)
Turnover	-0.709***	0.042***
	(0.107)	(0.005)
Ad&Promotion %	3.884	0.268
	(4.270)	(0.175)
Inst. Owner	0.292	-0.138***
	(0.514)	(0.041)
Analyst Coverage	0.153***	0.028***
	(0.059)	(0.003)
Instrument - *Media Experts' Ownership*		0.027***
		(0.007)
Industry FE	Included	Included
Year FE + Intercept	Included	Included
N	28,615	28,615
F-Stat		87.82
R^2		0.85

Stock-Yogo statistic	16.458
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.380

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