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Media Coverage and the Cross-section of Stock Returns

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ABSTRACT

By reaching a broad population of investors, mass media can alleviate informational frictions and affect security pricing even if it does not supply genuine news. We investigate this hypothesis by studying the cross-sectional relation between media coverage and expected stock returns. We find that stocks with no media coverage earn higher returns than stocks with high media coverage even after controlling for well-known risk factors. These results are more pronounced among small stocks and stocks with high individual ownership, low analyst following, and high idiosyncratic volatility. Our findings suggest that the breadth of information dissemination affects stock returns.

MASS MEDIA OUTLETS, such as newspapers, play an important role in disseminating information to a broad audience, especially to individual investors. Every weekday, some 55 million newspaper copies are sold to individual readers in the United States, reaching about 20% of the nation's population. If we consider online subscriptions and multiple readers per copy, the actual readership of the printed press is even larger, and certainly far broader than other sources of corporate information such as analyst reports. Given mass media's broad reach, one might expect it to affect securities markets. Interest in the relation between media and the market has been on the rise among both researchers and practitioners. Klibanoff, Lamont, and Wizman (1998), Tetlock (2007), and Tetlock, Saar-Tsechansky, and Macskassy (2008) are examples of this growing literature.[1]

We contribute to this strand of research by examining the cross-sectional relation between mass media coverage and stock returns. We find that stocks not covered by the media earn significantly higher future returns than stocks that are heavily covered, even after accounting for widely accepted risk characteristics. A portfolio of stocks with no media coverage outperforms a portfolio of

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[1] A detailed literature review appears in Section I.

stocks with high media coverage by 3% per year following portfolio formation after adjusting for market, size, book-to-market, momentum, and the Pastor-Stambaugh (2003) liquidity factor. The return difference is particularly large among small stocks, stocks with low analyst coverage, stocks primarily owned by individuals, and stocks with high idiosyncratic volatility. In these subsamples, the "no-media premium" ranges from 8% to 12% per year after risk adjustments. Thus, the return premium for stocks with no media coverage is economically significant.

The rational-agent framework provides two main explanations for the no-media premium in the cross-section. First, it may be a liquidity-related phenomenon. If the no-media premium reflects a mispricing (i.e., arbitrage), then profit-motivated traders will take positions to exploit and thereby eliminate this mispricing. Thus, a mispricing can persist only if market frictions are severe enough to prevent arbitrageurs from exploiting it. We call this the "impediments-to-trade" hypothesis. Alternatively, the no-media premium may represent compensation for imperfect diversification. The "investor recognition hypothesis" advanced by Merton (1987) posits that in informationally incomplete markets, investors are not aware of all securities. As a consequence, stocks with lower investor recognition need to offer higher returns to compensate their holders for being imperfectly diversified. By disseminating information to a wide audience, media coverage broadens investor recognition. Thus, stocks with intense media coverage earn a lower return than stocks in oblivion.

Our empirical tests provide support for both hypotheses. In particular, we find that the media effect is strong among small stocks and stocks with high bid-ask spreads. These results are consistent with the impediments-to-trade hypothesis. We also find that the no-media premium is particularly large among stocks that face the most severe information problems, that is, stocks with low analyst coverage, a high fraction of individual ownership, and high idiosyncratic volatility. These findings suggest that mass media's information dissemination role is particularly important among stocks for which information tends to be more "incomplete," consistent with Merton (1987). We note, however, that while impediments to trade may explain the persistence of the no-media premium, it does not explain why it arises in the first place. Thus, our conclusion is that the media effect is rooted in a Merton-type information story, and liquidity constraints help perpetuate the phenomenon.

The media effect is not subsumed by a host of well-documented return anomalies, including the postearnings announcement drift, IPO underperformance, and delisting bias. We also show that it is not driven by industry biases, differences in fundamental performance, and the bid-ask bounce. Finally, it is robust to different portfolio formation and holding periods. In particular, the return premium among no-coverage stocks is remarkably stable for at least 12 months.

Given publication delays, it is unlikely that information contained in mass print media is genuine news. But mass media does disseminate information to a broad audience. Thus, our finding on the role of the media indicates that the breadth of information dissemination affects stock returns. An interesting implication of our results is that noninformative channels such as mass media and even firms' public relation programs can affect firms' cost of capital. While market participants and company executives recognize that information dissemination plays a crucial role in determining the cost of capital, traditionally the focus has been on channels such as disclosure and stock analyst reports. In recent years, reforms in the securities industry, such as Reg FD and the Global Settlement between regulators and Wall Street research departments, have led to the (perhaps unintended) consequence that many stocks, including some listed on the NYSE, no longer enjoy analyst coverage. The *Wall Street Journal* has reported numerous anecdotes in which executives are concerned about the lack of analyst coverage on their stock and the adverse effect on their stock price. Our results indicate that for firms suffering from reduced analyst coverage, mass media coverage as well as firms' public relations efforts aimed at creating awareness and familiarity could pay off in terms of generating investor interest and reducing the cost of capital, especially in the post Reg FD environment.[2]

The remainder of the paper is organized as follows. Section I reviews the literature. Section II describes our data. Sections III and IV present and discuss the main empirical results. Section V concludes.

I. Literature Review

This paper is related to the literature on the relation between media and stock returns, and the literature on the cross-sectional pattern of stock returns.

A. *The Media and the Stock Market*

Earlier papers in this literature include Klibanoff et al. (1998), who showed that country-specific news reported on the front page of the *New York Times* affects the pricing of closed-end country funds. They find that during weeks of front-page news, price movements are more closely related to fundamentals. They therefore argue that news events lead some investors to react more quickly. More recently, Tetlock (2007) analyzes the linguistic content of the mass media and reports that media pessimism predicts downward pressure and a subsequent reversal. Tetlock et al. (2008) further document that the fraction of negative words used in news stories predicts earnings and stock returns. These findings suggest that qualitative information embedded in news stories contributes to the efficiency of stock prices.

Among papers that examine broadly defined media exposure, ours is the first that documents a cross-sectional relation between media coverage and security returns. Several recent papers document a positive relation between media and liquidity but fail to find significant return differentials. For example, Antweiler and Frank (2004) find that stock messages predict market volatility but their

[2] Reports confirm that companies are paying more attention to mass media after Regulation FD. According to a survey conducted in 2004 by Thomas L. Harris/Impulse Research, companies have increased spending on public relations by an average of 28% compared to that a year ago.

effect on returns is small. Grullon, Kanatas, and Weston (2004) document that firms with larger advertising expenditures have more liquid stocks. Frieder and Subrahmanyam (2005) report that individuals are more likely to hold stocks with strong brand recognition. Meschke (2004) finds that stocks experience a strong run-up and reversal during the 11 days after CEO interviews on CNBC. None of these papers finds persistent cross-sectional return patterns.[3]

Our paper is closely related to but distinct from Chan (2003), who examines momentum and reversal patterns following large price moves with and without accompanying news. Using data obtained mainly from the Dow Jones Newswire, Chan (2003) focuses on headline news. In contrast, we enumerate articles (not necessarily headlines) in mass-circulation newspapers and focus on coverage. We note that "news" and "coverage" are indeed different: Many stocks with news (headlines in the Dow Jones Newswire) remain neglected by mass media; in addition, while newswires are released in real time and contain genuine news, this is unlikely to be the case for mass print media due to publication lags. Another distinction is that Chan (2003) looks at market *reactions* to news in the time dimension (and the difference therein between winners and losers), whereas we examine the cross-sectional differences between stocks with and without coverage. We defer a more detailed discussion of the relation between our results and those in Chan (2003) to Section IV.

Our paper is also related to Barber and Odean (2008), who show that individual investors are net buyers of attention-grabbing stocks, for example, stocks in the news.[4] They argue that individuals face difficulties when choosing which stocks to buy from a large pool of candidates; thus, attention-grabbing stocks such as those in the news are more likely to enter their choice set. This buying pattern seems consistent with the media effect we document to the extent that individuals' buying pressure temporarily pushes up the prices of attention-grabbing (in-the-news) stocks, but such pressure subsequently reverses. Whether the media effect is driven by individual buying pressure is examined in Section III below.

B. The Determinants of Stock Returns in the Cross-section

Our paper is also related to the literature that analyzes the determinants of the cross-section of stock returns. Among recent studies in this literature, two papers are related to ours. Diether, Malloy, and Scherbina (2002) (DMS) document that stocks with higher analyst forecast dispersion yield lower future returns. Ang et al. (2006) (AHXZ) document that stocks with high idiosyncratic

[3] A separate stream of research represented by Mullainathan and Shleifer (2005) and Gentzkow and Shapiro (2006a, 2006b) studies media bias. In addition, an older literature examines market reactions to rumors featured in the popular "Heard on the Street" column in the *Wall Street Journal* (see, for example, Pound and Zeckhauser (1990)).

[4] In a related paper, Kumar and Lee (2006) show that individual investors trade in concert and that systematic retail trading explains return comovements for stocks with a high retail concentration. This paper leaves open the question of the origin of the systematic component of retail trades. Barber and Odean (2008) suggest that one source could be mass media coverage.

volatility (with respect to the Fama-French (1993) three-factor model) exhibit "abysmally" low returns. We find that media coverage is positively related to both analyst forecast dispersion and idiosyncratic volatility, after controlling for firm size.[5] Thus, our result that no-coverage stocks earn higher returns is consistent with both the DMS finding and the AHXZ finding. In Section IV, we discuss in more detail the relations between these results and show that the media effect is not subsumed under either effect.

Finally, another related paper is Easley, Hvidkjaer, and O'Hara (2002), who investigate whether information asymmetry between informed and uninformed traders is a determinant of asset returns. The authors propose and estimate a proxy for asymmetric information called PIN (Probability of Informed Trading) and show that it has incremental explanatory power for cross-sectional returns after controlling for size and book-to-market. Our analysis reveals that the media effect is not explained by PIN, suggesting that the media effect we document is not driven by information asymmetries between informed and uninformed traders.

II. Data and Descriptive Statistics

Our sample consists of all companies listed on the NYSE and 500 randomly selected companies listed on the NASDAQ between January 1, 1993 and December 31, 2002. The NYSE universe contains mainly large stocks. To the extent that large stocks enjoy good information dissemination, our sample is biased against finding any media effect. Following prior work, we exclude stocks with prices below $5 to ensure that results are not driven by small illiquid stocks or bid-ask bounce.

We use the number of newspaper articles about a stock to proxy for the stock's overall media exposure.[6] To collect this information, we systematically search the LexisNexis database for articles published in major U.S. newspapers that refer to the companies in our sample. We focus on four influential daily newspapers with nationwide circulation: *New York Times* (NYT), *USA Today* (USAT), *Wall Street Journal* (WSJ), and *Washington Post* (WP). With weekday circulation of about six million copies, these four newspapers account for 11% of total daily circulation in the United States.[7]

For each company in our sample, we obtain from LexisNexis its associated indexing keywords. We then manually match these company names with other

[5] Vega (2006) also documents that media coverage and analyst forecast dispersion are positively correlated.

[6] The rise of the internet in recent years as a mainstream media could have a large impact on the relevance of print media. Our sample ends in 2002, which diminishes this impact.

[7] Our sample includes four of the five most circulated newspapers in the United States. According to the Audit Bureau of Circulation, the WSJ, NYT, WP, and USAT had average daily circulations of 1.8, 1.1, 0.7, and 2.2 million paid copies, respectively (from April 1, 2002, to September 30, 2002). According to the Newspaper Association of America, the aggregate daily circulation of all newspapers is 55 million.

standard data sets.[8] LexisNexis uses a "relevance score" to measure the quality of the match between an article and a company. This score is based on criteria such as the keyword's frequency, and its weight and location within the document. To capture articles with a primary focus on a given company, we retain articles with a relevance score of 90% or above, which LexisNexis describes as "Major References." To obtain a time series of company-specific coverage, we take the weighted sum of articles published about each company in each month, where weights equal the newspapers' circulation in 2002, obtained from the Audit Bureau of Circulations.

We obtain stock return, market capitalization, and trading volume data from CRSP, and accounting data, such as book value of assets, from Compustat. Analyst coverage data are collected from I/B/E/S summary files. We measure analyst coverage for each firm and year in our sample by counting the number of analysts making fiscal year-end forecasts. We also estimate the fraction of individual ownership for each stock and year as 1 minus the fraction of total institutional ownership, obtained by aggregating 13f filings.

Table I provides summary statistics on the newspaper coverage of our sample stocks. Panels A, B, and C pertain to all, NYSE, and NASDAQ stocks, respectively. For brevity, Panel A reports annual statistics, whereas Panels B and C report average statistics over the entire period. We report both unconditional coverage statistics, namely, the fraction of firms covered by each source, and conditional statistics, namely, the number of newspaper articles per covered stock.

Several interesting observations can be made about media coverage patterns. First, overall newspaper coverage is surprisingly low. Even among NYSE stocks, which are generally large, over 25% are not featured in the press in a typical year. Coverage is even lower for NASDAQ stocks, with only about 42% of them receiving coverage in a given year. Second, the breadth of coverage differs considerably across newspapers. WSJ and NYT have the most comprehensive coverage, featuring 57% and 54% of NYSE stocks, respectively. WP and USAT have significantly less coverage. In particular, while NYT, WP, and USAT together cover 56% of firms, NYT alone covers 54%, indicating that the incremental coverage by WP and USAT is only 2%. Finally, the numbers also imply that there is considerable overlap—about 75%—in the different newspapers' coverage.[9] This overlap together with the low marginal contribution of widely circulated newspapers such as USAT and WP indicates that even though we focus on only four papers, our data are representative of the newspaper media. To the extent that coverage is correlated across media types, our data are also a reasonable proxy of overall media coverage.

[8] Data errors and omissions could create sampling error. LexisNexis tries to minimize this problem by associating each company with multiple keywords. For example, IBM is associated with both "IBM" and "International Business Machine."

[9] *Wall Street Journal* alone covers 59% of NYSE stocks. The three nonfinancial papers combined cover 57% of NYSE stocks (Panel B of Table II). But all four papers combined cover 73%, indicating that the overlap between WSJ and the nonfinancial papers is around 75%.

Table I

Summary Statistics of Newspaper Coverage

This table presents summary statistics for the newspaper coverage of our sample firms. Both unconditional statistics (percentage of firms receiving coverage) and conditional statistics (number of articles written on the firm conditioned on coverage) are presented. The column "All papers" refers to all four national newspapers in our sample: *Wall Street Journal* (WSJ), *New York Times* (NYT), *Washington Post* (WP), and *USA Today* (USAT). The column "Excl. WSJ" represents the three nonfinancial papers: NYT, WP, and USAT.

	Unconditional Coverage Statistics Fraction of Stocks Covered by						Conditional Statistics No. of Articles	
Year	All Papers	WSJ	Excl. WSJ	NYT	WP	USAT	Mean	Median
Panel A: All Stocks								
1993	0.77	0.61	0.60	0.58	0.12	0.07	11	4
1994	0.75	0.60	0.59	0.58	0.12	0.07	12	5
1995	0.75	0.61	0.60	0.59	0.11	0.07	11	5
1996	0.72	0.56	0.60	0.59	0.12	0.06	11	5
1997	0.73	0.56	0.61	0.59	0.13	0.06	11	5
1998	0.75	0.59	0.64	0.62	0.15	0.06	11	5
1999	0.68	0.58	0.50	0.47	0.15	0.04	12	4
2000	0.63	0.52	0.49	0.46	0.14	0.05	12	4
2001	0.62	0.52	0.44	0.42	0.14	0.05	12	4
2002	0.57	0.46	0.44	0.41	0.16	0.04	12	4
All years	0.70	0.57	0.56	0.54	0.13	0.06	12	5
Panel B: NYSE Stocks								
All years	0.73	0.59	0.59	0.57	0.14	0.06	12	5
Panel C: NASDAQ Stocks								
All Years	0.42	0.31	0.27	0.24	0.05	0.02	4.2	2

The conditional statistics in Table I reveal that coverage is highly skewed. The average number of articles published about a stock in a given year is 12, while the median is 5, and the maximum is 478. This pattern prevails for both NYSE and NASDAQ stocks, but the coverage statistics generally are three to four times larger for NYSE stocks than those for NASDAQ stocks.

Thus, there is a large difference between the "haves" and "have nots" in terms of media coverage. Transition matrices across coverage types confirm that media coverage is a persistent phenomenon: 83% of stocks with no media coverage in a given month are still absent from the media in the next month; 49% of stocks with high (above-medium) coverage continue to have high coverage in the next month. Persistence is even stronger among smaller stocks. These results suggest that media coverage (or the lack thereof) is a relatively stable firm characteristic. Notably, the sample stocks are all publicly listed firms, so the heterogeneity in media coverage in the cross-section cannot be driven by a drastically different amount of public disclosures such as earnings reports.

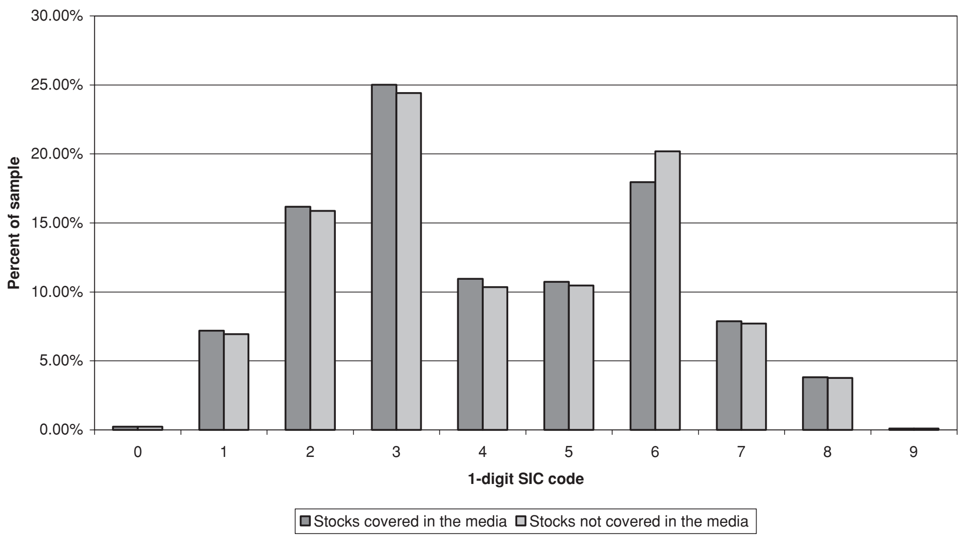

Figure 1. Industry distribution of media coverage. The histogram shows the industry distribution of stocks covered by the media and of stocks not covered by the media. The one-digit SIC classification is as follows—0: agriculture, forestry, and fishing; 1: mining and construction; 2: manufacturing (consumer goods); 3: manufacturing (machinery and equipment); 4: transportation and communications; 5: wholesale and retail; 6: finance; 7: business services; 8: health and education services; 9: public administration.

Is media coverage biased toward some industries? If this were the case, any cross-sectional return pattern we document could be a disguised industry effect. Figure 1 graphs the industry distributions for the no- and high-coverage stocks, and shows that they are virtually identical.[10]

Table II examines the determinants of media coverage in a regression setting. The dependent variable is the circulation-weighted number of articles published about a stock over a year.[11] We employ the Fama-MacBeth (1973) regression method. Because media coverage is persistent, we correct the standard errors for autocorrelation using the Newey-West (1987) procedure with one lag. We find that firm size has an overwhelming effect on media coverage: Large firms are much more likely to be covered. Controlling for size, firms with high book-to-market ratios, that is, value stocks, are also more likely to be featured in the media. Stocks covered by analysts are less likely to be in the media. This suggests that analyst coverage and media coverage are substitutes rather than complements. We also find that, all else equal, stocks with high individual ownership are more likely to be featured in the media. Thus, to the extent

[10] We repeated the analysis with finer, two-digit SIC codes, and the results are very similar.

[11] We obtain qualitatively similar results when we carry out a univariate analysis of the relation between media coverage and firm characteristics and a probit regression on media coverage. But we note that if the size is not controlled for, the sign on the book-to-market ratio becomes negative. This reflects the fact that size is strongly positively related to media coverage and negatively related to book-to-market in our sample.

Table II

Determinants of Media Coverage

This table reports Fama-Macbeth (1973) regression results on the determinants of media coverage. The dependent variable is the number of articles published about a stock in a given year. Independent variables are defined in Table AI. t-statistics are based on standard errors adjusted for autocorrelation using the Newey-West (1987) procedure with one lag. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: Number of Articles	
Size	1.084	1.081
	(20.17)**	(19.62)**
Book-to-market	0.233	0.228
	(12.06)**	(11.98)**
Analyst coverage	−0.518	−0.51
	(6.93)**	(6.86)**
Fraction of individual ownership	0.183	0.177
	(3.79)**	(3.77)**
Analyst dispersion	0.223	0.212
	(3.09)*	(2.50)*
Idiosyncratic volatility	42.364	42.668
	(6.35)**	(7.03)**
Past year absolute return	0.009	
	−0.08	
Past year return		−0.081
		−1.04
Constant	−14.167	−14.117
	(23.91)**	(23.54)**
Observations	13849.00	13849.00
R^2	0.24	0.24

that analysts tend to cater to institutional investors' information needs, the media seems to cater to individuals, after accounting for firm size. Finally, both analyst dispersion and idiosyncratic volatility are positively related to media coverage. Past returns have little impact on the likelihood of media coverage as both absolute and signed past returns are not significant in the estimation results.

III. Media Coverage and the Cross-section of Stock Returns

This section focuses on the cross-sectional relation between media coverage and stock returns. We first examine raw returns in univariate analysis, and then examine abnormal returns to account for various risk factors.

A. Univariate Analysis

Table III reports average returns of stocks double-sorted by firm characteristics and media coverage. We first sort stocks into terciles by various firm characteristics, such as size. Terciles are used to ensure adequate sample size

Table III

Media Coverage and Stock Returns: Univariate Comparisons

This table presents average monthly returns for stocks with no, low, and high newspaper coverage. Average return numbers are in percentages. Each month, we divide our sample of firms into three media-coverage portfolios: no coverage, low coverage, and high coverage. Media coverage is measured by the number of newspaper articles written about the company, and the median is used to divide the covered stocks into low and high groups. We then compute the equal-weighted average return of the three media coverage portfolios using individual stock returns in the next month. We also compute the return difference for subsamples of firms sorted on size, book-to-market ratio, current and past month returns, price, individual ownership, analyst coverage, illiquidity, and turnover. These variables are defined in Table AI.

	Average Monthly Return					Average No. of Stocks		
	Media Coverage				t-Statistics for	Media Coverage		
	No	Low	High	No − High	No − High	No	Low	High
All stocks	1.35	1.11	0.96	0.39	2.13	1,430.08	284.82	245.40
Panel A: By Size								
1	1.41	1.02	0.53	0.88	1.74	578.44	56.36	17.98
2	1.34	1.12	0.69	0.65	2.68	514.23	92.85	46.71
3	1.27	1.16	1.10	0.17	1.03	337.42	167.12	149.19
Panel B: By Book-to-Market								
1	1.19	0.95	0.87	0.32	1.25	441.79	93.98	81.50
2	1.23	1.17	0.54	0.70	3.13	450.03	92.90	74.64
3	1.42	1.10	1.19	0.22	0.85	460.78	86.20	70.57
Panel C: By Past Month Return								
1	1.43	0.98	0.85	0.58	2.29	474.54	93.31	76.78
2	1.25	0.89	0.91	0.34	1.73	461.16	97.56	82.13
3	1.09	1.07	0.64	0.44	2.19	467.33	93.25	78.77
Panel D: By Current Month Return								
1	1.96	1.49	0.86	1.10	4.24	479.50	94.11	75.77
2	1.29	1.08	1.01	0.28	1.36	475.29	94.21	79.54
3	0.88	0.75	1.08	−0.20	−0.76	467.93	100.31	84.40
Panel E: By Price								
1	1.01	0.53	−0.11	1.11	3.14	545.18	69.76	35.76
2	1.39	1.12	0.54	0.84	3.77	500.77	94.03	60.14
3	1.77	1.47	1.35	0.42	2.62	384.13	142.30	128.21

and diversification.[12] Next we sort each characteristic-based tercile into three media portfolios: no coverage, low coverage, and high coverage. Stocks with no newspaper coverage are first identified; the remaining stocks are divided into the low- and high-coverage groups using the median number of articles

[12] Terciles 1 and 3 refer to the lowest and highest value of each characteristic, respectively.

published. The equal-weighed return of each portfolio during the following month is then tabulated.[13]

The first row of Table III shows that unconditionally, the average monthly returns for stocks with no-, low-, and high-media coverage are 1.35%, 1.11%, and 0.96%, respectively. The difference between the no- and high-coverage groups is a statistically significant and economically meaningful 0.39% per month (4.8% per year). Thus, sorting stocks on media coverage alone generates a significant return differential in the cross-section, pointing to a return premium associated with no-coverage stocks. The double-sorts in Panels A–E control for firm characteristics one at a time and generally support the unconditional result. With only one exception, the return difference between no-coverage stocks and high-coverage stocks is positive, and in most cases significant. Therefore, there seems to be a pervasive no-coverage premium among stocks, even holding various firm characteristics constant.

Interestingly, Panel D of this table shows that the no-media premium is found only among low current return (i.e., loser) stocks (tercile 1). This is consistent with the finding in Chan (2003) that loser stocks with contemporaneous news experience negative return drift and loser stocks without news tend to reverse subsequently. Chan also finds no such drift nor reversal for winner stocks. This suggests that our media effect could be related to the phenomena documented by Chan (2003). We return to this point in much greater detail in Section IV below when we explore the explanations of the media effect.

B. Multivariate Analysis

To examine the media effect controlling for risk factors, we form long–short portfolios of stocks sorted by media coverage. Each month, we divide the stock sample into no-media, low-media, and high-media coverage groups as before. We then compute the return in the following month on a zero-investment portfolio that longs the stocks with no media coverage and shorts the stocks with high media coverage. Repeating this every month yields a time series of returns for this zero-investment portfolio. The time-series returns are then regressed on factors known to affect the cross-section of returns. We examine four different factor models: the market model, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that includes the Pastor-Stambaugh (2003) liquidity factor. The Pastor-Stambaugh liquidity factor controls for stocks' exposure to the aggregate (market-wide) liquidity risk. Stock-specific liquidity, such as bid-ask spread, is examined in detail in the next section. If the return difference between no-coverage and high-coverage stocks is fully explained by known factors, then the estimated alpha should be insignificant.

Table IV reports the baseline result in this multivariate setting. The table confirms the earlier univariate finding that there is a no-media return

[13] Equal-weighted returns have been used in Chan (2003), Diether, Malloy, and Scherbina (2002), and Kumar and Lee (2006), among others.

Table IV

Media-Related Trading Profits: Baseline Multivariate Results

This table examines the profitability of a trading strategy that longs stocks with no media coverage and shorts stocks with high media coverage. Each month, stocks are sorted according to the number of newspaper articles published about them. A stock is considered to have no media coverage if no article is published about the stock in a given month. A stock is considered to have high coverage if the number of articles about it exceeds the medium in a given month. Both the long and short positions are equally weighted, and held for 1 month after portfolio formation. Portfolios are rebalanced monthly. The resulting time-series returns on the long–short portfolio are regressed on widely accepted risk factors (defined in Table AI), and the results are reported. *p*-values are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor	Model 4: PS Liquidity
Panel A: Long No-Media Stocks, Short High-Media Stocks				
Mkt-rf	−0.1434***	−0.1182***	−0.0910***	−0.0918***
	(0.0002)	(0.0004)	(0.0053)	(0.0050)
SMB	–	0.3719***	0.3565***	0.3602***
		(0.0000)	(0.0000)	(0.0000)
HML	–	0.1580***	0.1732***	0.1620***
		(0.0004)	(0.0001)	(0.0003)
UMD	–	–	0.0767***	0.0939***
			(0.0006)	(0.0017)
LIQ	–	–	–	−2.5419
				(0.3783)
Intercept	0.0045**	0.0035***	0.0024**	0.0023*
	(0.0110)	(0.0051)	(0.0471)	(0.0611)
Observations	119	119	119	119
R^2	0.11	0.58	0.62	0.62
Panel B: Alphas for No-Media Coverage Stocks				
Intercept	0.0065***	0.0024	0.0042***	0.0039***
	(0.0072)	(0.1020)	(0.0023)	(0.0047)
Panel C: Alphas for High-Media Coverage Stocks				
Intercept	0.002	−0.0011	0.0018	0.0016
	(0.3263)	(0.4749)	(0.1263)	(0.1859)

premium even after controlling for market, size, book-to-market, momentum, and liquidity factors. However, the factor models do explain a significant portion of the premium, as the alphas successively decrease when factors are added. The alpha in the five-factor model is 23 basis points per month, compared to 45 basis points in the market model, indicating that about half of the alpha relative to the market model is absorbed by commonly known risk factors.[14]

[14] We also repeat the analysis splitting our sample period into two subperiods, 1993 to 1997 and 1998 to 2002. The results are qualitatively similar in both subperiods (no-coverage stocks generate significant positive alphas relative to high-coverage stocks), albeit statistically stronger in the first

The loadings on the risk factors are interesting. The positive and significant coefficients on the size factor (SMB), the book-to-market factor (HML), and the momentum factor (UMD) indicate that the zero-investment strategy of buying no-media coverage stocks and shorting high-media coverage stocks has a positive exposure to small stocks, value stocks, and momentum stocks. The strategy has a negative exposure to overall market movements, as indicated by the negative sign on the market factor. This is because our portfolio strategy is zero investment, and the stocks sold short (those with high media coverage) tend to co-move more with the market than stocks held long (those with no media coverage).

Panels B and C of Table IV investigate the long (no-coverage stocks) and short (high-coverage stocks) legs of the portfolio separately. The results here show that the media effect is primarily driven by the long positions in the stocks without media coverage. High-coverage stocks, in contrast, do not exhibit significant alphas.[15] This asymmetry indicates that stocks neglected by the media earn a significant return premium, and this causes the observed media effect.

Interestingly, this asymmetry also suggests that the media effect is unlikely to be caused by individual (or generally unsophisticated) investors' buying of attention-grabbing stocks. Barber and Odean (2008) document that individuals exert buying pressure on attention-grabbing stocks such as those in the news. These stocks subsequently underperform. If the media effect is caused by this phenomenon, we expect the long–short strategy alpha to come from the short leg (high-coverage stocks). But this is not the case. On the contrary, the media effect stems from those stocks in oblivion that earn abnormally high returns. We will examine the cause of this in detail in Section IV below.

We also use the characteristic-based benchmark method in Daniel et al. (1997) (DGTW) to check our results. The benchmark returns are based on portfolios matched on size, book-to-market, and momentum.[16] In unreported analysis, we find that the difference in benchmark-adjusted returns between no-coverage stocks and high-coverage stocks is 29 basis points per month (t-statistic = 3.34). In addition, it is the no-coverage stocks that continue to exhibit positive and significant alphas: The DGTW benchmark-adjusted returns are 23 basis points per month (t-statistic = 6.63) for these stocks, and −6 basis points (t-statistic =

subperiod. Lower statistical significance in the second sub-period seems to be caused by a higher overall return volatility.

[15] The fact that both the long and short legs of the portfolios display positive alphas—though not significantly so for high-media coverage stocks—reflects both the equal-weighting scheme used to compute portfolio returns and the limited number of stocks in our sample, which consists mostly of NYSE stocks. Indeed, we find that stocks with a low media coverage (the remaining middle-portfolio stocks not used in the portfolio strategy) also exhibit a positive alpha on average: It equals, respectively, 0.0038, 0.0001, 0.0022, and 0.0019 in models 1–4. Importantly, alphas are monotonically decreasing in the amount of media coverage, which is consistent with the Merton hypothesis.

[16] We thank the authors of DGTW (1997) for making the benchmark data available via Russ Wermer's website at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

Table V

Media-Related Trading Profits by Firm Characteristics

This table examines the profitability of a media-based trading strategy in subsamples of firms sorted by various firm characteristics. Each month, stocks are sorted into three media coverage portfolios: no coverage, low coverage, and high coverage. Stocks with no media coverage are first identified, and then the remaining stocks are divided into low- and high-coverage groups by the median number of newspaper articles published about that stock. The portfolio then goes long on the stocks with no media coverage and short on stocks with high media coverage in the next month. The long and short legs of the portfolio invest an equal amount in each underlying stock, and portfolio weights are rebalanced monthly. Reported number are alphas from regressing the resulting time series of zero-investment portfolio returns on the market factor, the Fama-French (1993) three-factor, Carhart (1997) four-factor, and Pastor-Stambaugh (2003) liquidity factor models. p-values are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

CAPM	FF Three-Factor	Carhart Four-Factor	PS Liquidity
Panel A: By Firm Size			
Small			
0.0103**	0.0108**	0.0082	0.0076
(0.0375)	(0.0349)	(0.1141)	(0.1443)
Medium			
0.0069***	0.0064***	0.0045*	0.0043*
(0.0046)	(0.0094)	(0.0651)	(0.0802)
Large			
0.0023	0.0014	−0.0004	−0.0006
(0.1418)	(0.3771)	(0.7651)	(0.6815)
Panel B: By Book-to-Market			
Low			
0.0078***	0.0065***	0.0048**	0.0046**
(0.0003)	(0.0010)	(0.0128)	(0.0181)
Medium			
0.0035	0.0033*	0.0017	0.0016
(0.1223)	(0.0988)	(0.4005)	(0.4132)
High			
0.0047*	0.0039*	0.0025	0.0027
(0.0774)	(0.0750)	(0.2510)	(0.2246)
Panel C: By Past 12-Month Momentum			
Low			
0.0064**	0.0061**	0.0040*	0.0043*
(0.0196)	(0.0150)	(0.0997)	(0.0780)
Medium			
0.0056***	0.0045***	0.0044***	0.0040***
(0.0092)	(0.0026)	(0.0044)	(0.0092)
High			
0.0050**	0.0037*	0.0040*	0.0035
(0.0403)	(0.0868)	(0.0769)	(0.1181)

−0.33) for high-media stocks. These results are consistent with the regression results.

Table V examines the media effect in subsamples sorted by size, book-to-market (B/M), and 12-month return momentum. In this analysis, within each tercile, the relevant characteristic is controlled for in two ways: by sorting and by an explicit regression control. The goal of this analysis is to identify the subsets of stocks in which the media effect is the strongest. Table V shows that the media effect is concentrated among small stocks (Panel A) and low B/M stocks (Panel B). It is also stronger among stocks with low past returns (Panel C), but the difference across the momentum terciles is not as dramatic as that in the univariate results in Panel D of Table III.

The fact that the media effect is strongest among small stocks raises the concern that the media effect is spurious, as many documented return anomalies occur among small firms. Two specific concerns are that (1) the media effect could be driven by bid-ask bounce, which affects the measurement of small stock returns, and (2) the media effect could be a misnamed size effect. Regarding the first concern, we note that our sample consists mainly of NYSE stocks, which are far larger and more liquid than the overall CRSP universe.[17] In addition, we have dropped stocks with prices below $5, making it less likely that the no-media premium is caused by bid-ask bounce among small stocks. Furthermore, in robustness checks below, we compute returns from bid-ask midpoints and find results that are quantitatively and qualitatively similar to the baseline. Regarding the second concern, it is important to interpret the test in Table V correctly. If the media coverage sort were simply a disguised sort on size, then the media effect should disappear within each size tercile. In our experiment, stocks within each size tercile are relatively homogenous in size but differ significantly in media coverage. We find a strong media effect *among* the smallest set of stocks and no effect *among* the largest set. Because smaller stocks *as a group* tend to have poorer information dissemination compared to larger stocks, the *asymmetry* between small and large stocks suggests that mass media plays a bigger role when information dissemination is otherwise poor; for large stocks, which already have many information channels, the role of mass media is limited.

C. Robustness

In this section, we conduct a number of robustness checks on the baseline results presented in Tables IV and V. In particular, we try to alleviate the concern that the media effect could be driven by (a) bid-ask bounce, (b) postearnings announcement drift, (c) delisting bias, (d) IPO underperformance, and (e) sector bias.

Monthly returns based on closing prices are used in the baseline analysis. This could lead to a bias induced by bid-ask bounce if some stocks are thinly traded. This is a relevant concern as we find that the media effect is more

[17] For example, the mean (median) equity market capitalization is $4.7B ($947M) for NYSE stocks, compared to $1.9B ($198M) for all CRSP stocks. The mean (median) monthly trading volume is $352M ($59M) for NYSE stocks compared to $223M ($14M) for all CRSP stocks. The mean (median) bid-ask spread using monthly closing data is 1.83% (1.43%) for NYSE stocks compared to 2.83% (1.96%) for all CRSP stocks.

Table VI
Robustness Checks

This table reports returns of a long–short portfolio that goes long on stocks with no media coverage in the previous month and goes short on stocks with high (above median) media coverage in the previous month, after applying various data screens. The long and short legs of the portfolio invest an equal amount in each underlying stock. *p*-values are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor	Model 4: PS Liquidity Factor
Panel A: Returns Based on Bid-Ask Midpoints				
Intercept	0.0051***	0.0043***	0.0030**	0.0029**
	(0.0051)	(0.0010)	(0.0159)	(0.0195)
Panel B: Excluding Earnings Announcements				
Intercept	0.0056***	0.0049***	0.0046***	0.0046***
	(0.0017)	(0.0035)	(0.0082)	(0.0080)
Panel C: Excluding IPOs				
Intercept	0.0046***	0.0033***	0.0021*	0.002
	(0.0086)	(0.0081)	(0.0789)	(0.1036)
Panel D: With Corrected Delisting Returns				
Intercept	0.0045**	0.0035***	0.0024**	0.0023*
	(0.0109)	(0.0047)	(0.0470)	(0.0607)
Panel E: Applying All Three Filters (B–D)				
Intercept	0.0053***	0.0044**	0.0039**	0.0039**
	(0.0038)	(0.0133)	(0.0332)	(0.0343)
Panel F: Excluding Tech-Sector Stocks				
Intercept	0.0038**	0.0035***	0.0031***	0.0031***
	(0.0264)	(0.0022)	(0.0086)	(0.0097)

concentrated among smaller stocks. To check this possibility, we repeat our analysis using monthly returns based on bid-ask midpoints, rather than transaction prices. Panel A of Table VI shows that results based on bid-ask midpoints are similar to and indeed slightly stronger than the baseline results. Thus, we conclude that our result is not driven by microstructure issues such as bid-ask bounce.

Postearnings announcement drift, IPO underperformance, and delisting bias are well-documented return anomalies and hence we need to check that the media effect is not driven by them. These anomalies could lead to a spurious media effect if media coverage is more intense for firms announcing earnings, for IPO stocks, or for stocks going through delisting. For example, if media coverage is biased toward bad earnings news, or if returns tend to drift more following bad earnings news compared to good earnings news,[18] then indeed a strategy that longs no-coverage stocks and shorts high-coverage stocks will generate a positive alpha. A no-coverage premium would also result if high-coverage stocks are disproportionally represented by IPO stocks that subsequently underperform. Finally, if media has a tendency to cover firms going through delisting for negative reasons (for example, liquidation or takeover), then the delisting bias reported by Shumway (1997) could also lead to a spurious media effect.[19]

To check that our results are not driven by postearnings announcement drift or IPO underperformance, we exclude all potentially earnings-related media coverage[20] and all IPO stocks. To check that our results are not driven by delisting bias, we follow Shumway (1997) and replace all missing delisting returns with −30% for delisting codes of 500 or 520–584. Results for these robustness checks are reported in Panels B, C, and D of Table VI, respectively, and they show that the media effect is robust to these alternative specifications. When all three filters are simultaneously applied (Panel E), the results remain qualitatively and quantitatively similar to the baseline.

Finally, we check that our results are not driven by the tech sector, which experienced a dramatic rise and fall during our sample period. For this purpose, we exclude all tech-sector stocks from our sample.[21] Panel F shows that the media effect is robust and strong in the remaining nontech sector. Thus, it is not a tech-sector phenomenon. We also investigate whether the return difference between high- and no-coverage stocks is simply driven by differences in operating performance. We fail to find support for this conjecture (unreported).[22] We conclude that the media effect is not caused by a number of known return anomalies.

IV. Explaining the Media Effect

In this section, we discuss three possible causes of the media effect: continuations and reversals in returns, lack of liquidity, and information frictions.

[18] Both of these conjectures, however, are not borne by the data. Hayn (1995) finds that returns are more sensitive to positive earnings surprises than to negative ones. Moreover, in our sample, stocks in the media are just as likely to experience positive returns as negative returns in the month contemporaneous with media coverage, so mass media does not seem to exhibit a bias.

[19] Shumway (1997) reports that the CRSP database has a systematic upward bias on returns of certain delisted stocks. This is because negative delisting returns are coded as missing when the delisting is due to performance reasons.

[20] We consider any media coverage in months that a firm reports earnings as potentially earnings related. Excluding these articles reduces our media sample by about 40%. Thus, earnings announcements seem to account for a large proportion of routine coverage.

[21] We use the tech/non-tech classification based on SIC codes and PERMNOs in Loughran and Ritter (2004).

[22] We examine two operational performance measures: return on equity, defined as income before extraordinary items over book equity, and return on assets, defined as income before extraordinary items over total assets. We compare both levels and changes of these measures for firms with and without media coverage, and fail to find significant differences.

A. Return Continuations and Reversals

One possibility is that the media effect we document is a transient phenomenon caused by short-term return continuations or reversals. Chan (2003) documents that stocks with low returns during months when firms have headline news (he calls these stocks "news losers") experience negative return drift for over 12 months.[23] In contrast, "no-news losers" (i.e., stocks that have low returns during months without accompanying news) see their returns reverse.[24]

These patterns could generate the result that no-coverage stocks have higher returns than high-coverage stocks, to the extent that no-coverage stocks correspond to "no news stocks" and high-coverage stocks to "news stocks." In this case, our long–short strategy will be equivalent to buying no-news stocks and shorting news stocks, and given the reversal among no-news stocks (losers in particular) and drift among news stocks (losers in particular), such a strategy would generate a positive alpha, consistent with our results. Since the reversal and drift effects documented by Chan (2003) are concentrated among losers, there is a concern that our results represent the same reversal/drift patterns, especially since Panel D of Table III suggests that the media effect is stronger among losers.[25]

Relating to Chan (2003), we first note that "news" and "coverage" are in fact markedly different. While 92% of our high-coverage stocks have contemporaneous headline news, so do 76% of our no-coverage stocks.[26] Thus, many companies with news continue to be neglected by mass media. This means that equating the new/no-news classification in Chan (2003) and the coverage/no-coverage classification in this paper is inaccurate.

We now investigate whether the media effect is due to either (a) negative return drift among high-coverage losers or (b) return reversal of no-coverage losers. Scenario (a) can be ruled out because the alpha on the long–short portfolio stems primarily from the long leg (no-coverage stocks). If the media effect were caused by negative drift among high-coverage losers, then the alpha of the long–short portfolio should primarily come from the short leg (high-coverage

[23] There is no strong drift, however, for "news winners." Drift among "news losers" is consistent with the "bad news travels slowly" idea in Hong, Lim, and Stein (2000).

[24] Chan finds no reversal among "no-news winners." In other words, the drift and reversal effects in Chan (2003) are both concentrated among losers.

[25] However we note that once multiple risk factors are controlled for, Panel C in Table V shows that the no-media premium exists in winners as well as losers, albeit slightly stronger among losers.

[26] We thank Wesley Chan for making some of his data available to us for comparison. Further analysis reveals that Chan's media data have overall more "hits" per stock than our data. This is due to a larger set of sources used by Chan, which include in particular the Dow Jones Newswire service. Interestingly, Chan's data cover disproportionally more loser stocks, small stocks, and stocks with earnings news. Statistics pertaining to these comparisons are available from this article's Internet Appendix available at http://www.afajof.org/supplements.asp.

Table VII

Different Formation Periods and Holding Periods

This table reports mean returns for the long–short portfolio that goes long on stocks with no media coverage over the past N months (the "formation period") and short on stocks with high (above-median) media coverage over the past N months ($N = 1, 3, 6$). Average monthly alphas for various holding horizons between 1 month and 12 months are reported (the "holding period"). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Holding Period	Time-Series Mean	CAPM Alpha	FF Three-Factor Alpha	Carhart Four-Factor Alpha	PS Five-Factor Alpha
Panel A: Formation Period = 1 Month					
1 month	0.0039**	0.0045**	0.0035***	0.0024**	0.0023*
3 months	0.0033*	0.0039**	0.0028**	0.0016	0.0015
6 months	0.003	0.0036**	0.0026**	0.0013	0.0012
9 months	0.0026	0.0033*	0.0024**	0.0012	0.0011
12 months	0.0027	0.0034*	0.0025**	0.0013	0.0011
Panel B: Formation Period = 3 Months					
1 month	0.0036**	0.0042**	0.0033***	0.0022**	0.0020*
3 months	0.0032*	0.0038**	0.0030***	0.0017	0.0015
6 months	0.0029	0.0035**	0.0028**	0.0016	0.0015
9 months	0.0028	0.0035**	0.0029***	0.0017*	0.0015
12 months	0.0028	0.0034*	0.0030***	0.0017*	0.0016
Panel C: Formation Period = 6 Months					
1 month	0.0032*	0.0038**	0.0032***	0.0022**	0.0021**
3 months	0.0029	0.0034**	0.0030***	0.0021**	0.0020**
6 months	0.0027	0.0033*	0.0030***	0.0021**	0.0020*
9 months	0.0027	0.0033*	0.0032***	0.0022**	0.0021**
12 months	0.0028	0.0035*	0.0033***	0.0022**	0.0021*

stocks) of the strategy. But Table IV shows that alphas are indistinguishable from zero among high-coverage stocks.[27]

To evaluate the possibility that the media effect is caused by return reversals among no-coverage stocks, we examine the effect's horizon. The idea is as follows. Chan (2003) documents that the reversal pattern among no-news losers is short-lived: Among stocks priced above $5 (similar to our sample), the reversal is very weak and only found in the first month after portfolio formation. Thus, if reversal explains our result, we expect it to be short-lived as well. Accordingly, we examine the alphas of our long–short strategy for postformation holding periods ranging from 1 to 12 months and report the findings in Table VII. We use the calendar-time overlapping portfolio approach of Jegadeesh and Titman

[27] Table IV shows that high coverage stocks actually exhibit positive alphas, although they are generally insignificant. The fact that both the long and short legs of the strategy exhibit positive alphas in terms of magnitude is a result of equal weighting and our sample stocks constituting only a subsample of the CRSP universe. If Chan's results explain ours, however, we'd expect *negative* alphas among high-coverage stocks, which is not the case.

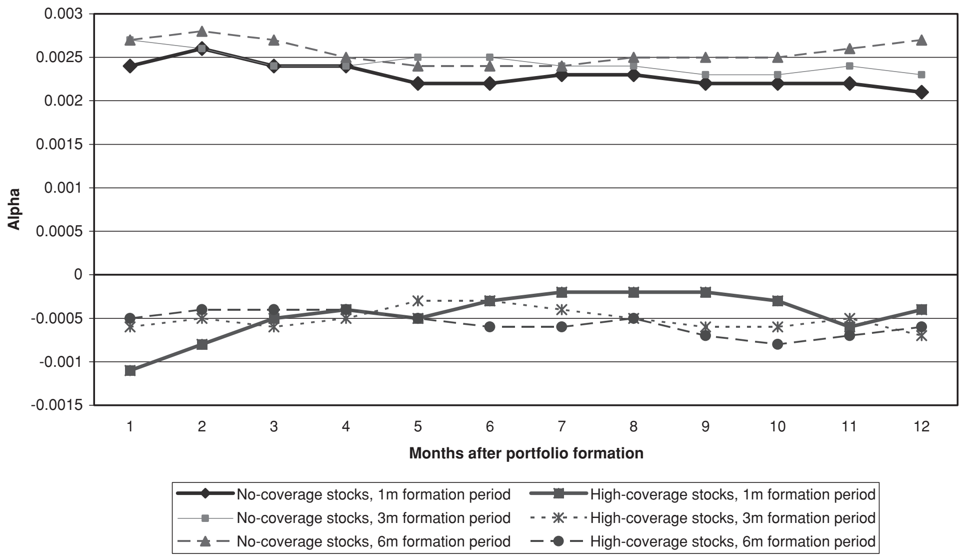

Figure 2. Horizon analysis of the media effect. Fama–French three-factor adjusted alphas for no- and high-coverage stocks are displayed for various formation and holding periods. Stocks are assigned to portfolios based on their coverage in the media over the past 1, 3, or 6 months. The portfolio returns are plotted for holding horizons ranging from 1 month to 12 months.

(1993) to calculate postformation returns.[28] For brevity, only select holding period results are tabulated. We form portfolios based on 1-month media coverage (Panel A, as in our baseline analysis), as well as 3- and 6-month media coverage (Panels B and C).

This table shows that the Fama-French three-factor alpha of our long–short strategy persists far beyond the 1-month horizon (three-factor alphas are comparable to Chan (2003) who adjusts for size and book-to-market ratios. Our conclusion does not change when four-factor alphas are used). Corroborating this conclusion, Figure 2 graphs the alphas of the long and short legs separately, and indicates not only that the alphas on the long–short strategy stem from the long (no-coverage) leg, as we have noted above, but also that they are remarkably stable. These patterns suggest that our results are not driven by short-term reversals among no-coverage stocks.

In addition, both Table VII and Figure 2 also show that the media effect is more stable when a longer formation period is used. In particular, while the momentum factor reduces the alpha's significance in the 1-month formation

[28] This approach has been widely adopted in the finance literature. See, among others, Fama (1998), Diether, Malloy, and Scherbina (2002), and Chan (2003). Fama (1998) indicates that "The time-series variation of the monthly abnormal return on this portfolio accurately captures the effects of the correlation of returns across event stocks missed by the model for expected returns. The mean and variance of the time series of abnormal portfolio returns can be used to test the average monthly response of the prices of event stocks . . . following the event" (p. 295).

case (Panel A, baseline), it remains stable and strong 12 months postformation with four-factor adjustments when the longer formation period of 6 months is used.

In summary, the results in this section suggest that the media effect is not caused by short-term reversal and continuation patterns widely discussed in the literature and documented in Chan (2003). Instead, it is a stable cross-sectional return difference the cause of which is examined further below. We also show that "news" and "coverage" are different, as many stocks with news remain neglected by the media (as do many stocks without news).

B. The "Impediments to Trade" Hypothesis

The rational agent framework offers two explanations for the cross-sectional return differential we document.[29] If the media effect represents an arbitrage opportunity, it can only persist if large impediments prevent rational agents from trading on it. We call this the "impediments-to-trade" or "illiquidity" hypothesis. Alternatively, the return differential may not reflect a mispricing but a fair compensation for risks not captured by standard factors. We examine these two explanations in turn.

To test the impediments-to-trade hypothesis, we examine its cross-sectional predictions. If impediments to trade explain the media effect, then the media-based abnormal profits should be concentrated among the most illiquid stocks. In Table VIII, we sort stocks into groups based on various liquidity proxies and report the long–short alphas for each group. We examine four liquidity proxies: the Amihud (2002) illiquidity ratio, bid-ask spread, dollar trading volume, and price.

The results in Table VIII provide mixed evidence. Sorting stocks by bid-ask spread (Panel B) provides the strongest support for the illiquidity hypothesis: This panel shows that the media effect is strongest among stocks with the highest bid-ask spread. Sorting by price (Panel D) results in significant alphas in all three price ranges, but the magnitude of the media effect is the largest among low-priced stocks, consistent with the illiquidity hypothesis. The implications of sorts by the Amihud illiquidity ratio and daily trading volume are less clear. For both measures, we find that the media effect is most pronounced among stocks with a medium level of liquidity; in fact, the effect actually disappears among the most illiquid stocks by these measures, when the theory suggests that it should be the strongest.

We can estimate how much liquidity is needed to dissipate the alpha as an additional check on the illiquidity hypothesis. The Amihud ratio, calculated as a stock's absolute daily return divided by its daily trading volume (scaled by 10^6), is a price impact measure. For stocks that exhibit the strongest media effect (the medium group in Panel A), the average value of this ratio is 0.016,

[29] Alternatively, the media effect could be driven by behavioral stories. We do not investigate this class of explanations formally in this paper. We note, however, in Section III B that it is unlikely to be caused by attention-induced buying pressure as in Barber and Odean (2008).

Table VIII
Illiquidity and the Media Effect

This table examines the profitability of a media-based trading strategy in subsamples of firms sorted by various liquidity measures. Monthly alphas from various factor models of a long–short strategy that goes long no-coverage stocks and short high-coverage stocks in the previous month are reported. Equal weights are used in each leg, and portfolios are rebalanced monthly. The liquidity measures are defined in Table AI. *p*-values are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

CAPM	FF Three-Factor	Carhart Four-Factor	PS Liquidity
Panel A: By Amihud's (2002) Illiquidity Ratio			
Low			
0.0025	0.0016	−0.0004	−0.0005
(0.1162)	(0.3202)	(0.7609)	(0.7281)
Medium			
0.0113***	0.0119***	0.0097***	0.0093***
(0.0001)	(0.0000)	(0.0007)	(0.0012)
High			
0.0046	0.0035	0.0021	0.0022
(0.3084)	(0.4574)	(0.6603)	(0.6477)
Panel B: By Bid-Ask Spread			
Low			
0.0001	−0.001	−0.0012	−0.0012
(0.9433)	(0.5113)	(0.4694)	(0.4781)
Medium			
0.0096***	0.0084***	0.0074***	0.0071***
(0.0000)	(0.0000)	(0.0003)	(0.0005)
High			
0.0098***	0.0096***	0.0086***	0.0095***
(0.0010)	(0.0009)	(0.0039)	(0.0010)
Panel C: By Dollar Trading Volume			
Low			
0.0063	0.0089*	0.0066	0.0056
(0.1815)	(0.0641)	(0.1802)	(0.2494)
Medium			
0.0090***	0.0084***	0.0070**	0.0073**
(0.0035)	(0.0077)	(0.0278)	(0.0240)
High			
0.0047**	0.0041**	0.0023	0.0022
(0.0129)	(0.0243)	(0.1805)	(0.2056)
Panel D: By Price			
Low			
0.0128***	0.0132***	0.0099***	0.0101***
(0.0001)	(0.0001)	(0.0015)	(0.0014)
Medium			
0.0090***	0.0083***	0.0054***	0.0053***
(0.0001)	(0.0002)	(0.0065)	(0.0084)
High			
0.0045***	0.0035***	0.0024*	0.0023*
(0.0049)	(0.0067)	(0.0595)	(0.0747)

meaning that a \$1M trade triggers a 1.6% price impact. Given a four-factor alpha of 0.98% in this group, it would take a trade of 0.98%/1.6% = \$0.61M to eliminate the profit over a single day. This is a large amount according to common classifications of "large" and "small" trades.[30] In addition, Panel C shows that the media effect is strongest among stocks with a medium level of trading volume. The average daily trading volume is about \$2M for these stocks, which is equal to the median daily volume among NYSE stocks. These numbers suggest that the market is deep enough to support arbitrage trades, thus casting some doubt on whether impediments to trade explain the media effect in practice.

C. The Investor Recognition Hypothesis

Merton (1987) offers an alternative explanation to the media effect within the rational agent paradigm. He models informationally incomplete markets in which investors only know about a subset of the available stocks. In such markets, stocks that are recognized by fewer investors need to offer higher returns to compensate their holders for being imperfectly diversified. This hypothesis, known as the "investor recognition hypothesis," has particular relevance to the media effect. Mass media, by reaching a broad audience, can increase the degree of investor recognition of a stock (even if it does not provide genuine news).

If media coverage improves investor recognition, then its effect should be stronger among stocks that otherwise have a lower degree of recognition. We test this hypothesis by sorting stocks on variables that reflect the degree of information incompleteness. Our information proxies include analyst coverage and the fraction of individual ownership. We conjecture that low analyst coverage and a high fraction of individual ownership characterize stocks with poor information dissemination, so we expect the media effect to be particularly strong among these stocks. In addition, in Merton's (1987) framework, firms' idiosyncratic risk is priced because of the imperfect diversification that stems from a lack of investor recognition. Firms with higher idiosyncratic volatility should offer a return premium to compensate shareholders for the undiversified risk they impose. This suggests two additional proxies that indicate the cost of poor investor recognition: idiosyncratic volatility and the ratio of idiosyncratic volatility to the number of shareholders (obtained from 13f filings). The former measures the amount of idiosyncratic risk borne by investors due to imperfect diversification; the latter measures the same amount on a per-investor basis. Following Ang et al. (2006), we estimate firms' idiosyncratic volatility as the standard deviation of daily abnormal stock returns relative to the Fama-French three-factor model. If media coverage increases investor recognition and improves diversification, its effect should be stronger among firms with higher idiosyncratic volatility and higher idiosyncratic volatility per shareholder.

Table IX reports the media effect among stocks sorted by our information proxies. The results here provide broad support for the investor recognition

[30] For example, Hvidkjaer (2006) suggests \$3,400, \$4,800, \$7,300, \$10,300, and \$16,000 as cutoffs for "small trades" for NYSE/AMEX quintiles.

Table IX

Investor Recognition and the Media Effect

This table examines the profitability of a media-based trading strategy in firms sorted by investor recognition. Monthly alphas from various factor models of a long–short strategy that goes long no-coverage stocks and short high-coverage stocks in the previous month are reported. Equal weights are used in each leg, and portfolios are rebalanced monthly. The investor recognition measures are defined in Table AI. p-values are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

CAPM	FF Three-Factor	Carhart Four-Factor	PS Liquidity
Panel A: By Analyst Coverage			
No			
0.0069	0.0072	0.0078*	0.0082*
(0.1142)	(0.1007)	(0.0866)	(0.0748)
Low			
0.0081***	0.0077***	0.0070***	0.0067***
(0.0001)	(0.0003)	(0.0014)	(0.0023)
High			
0.0015	−0.0001	−0.0015	−0.0018
(0.4048)	(0.9701)	(0.3639)	(0.2736)
Panel B: By the Fraction of Individual Ownership			
Low			
0.0025	0.0011	0.0001	0
(0.2121)	(0.4586)	(0.9371)	(0.9997)
Medium			
0.0061***	0.0042**	0.0024	0.0021
(0.0078)	(0.0200)	(0.1629)	(0.2383)
High			
0.0089***	0.0101***	0.0094***	0.0093***
(0.0014)	(0.0001)	(0.0006)	(0.0008)
Panel C: By Idiosyncratic Volatility			
Low			
0.0000	−0.0002	0.0002	0.0008
(0.9984)	(0.8557)	(0.8637)	(0.5644)
Medium			
0.0040**	0.0022	0.0016	0.0015
(0.0349)	(0.1324)	(0.2959)	(0.3205)
High			
0.0096***	0.0090***	0.0060**	0.0062**
(0.0018)	(0.0034)	(0.0421)	(0.0359)
Panel D: By Idiosyncratic Volatility per Investor			
Low			
0.0018	−0.0002	−0.0014	−0.0018
(0.2447)	(0.8612)	(0.2838)	(0.1774)
Medium			
0.0056*	0.0060*	0.0024	0.0025
(0.0654)	(0.0538)	(0.4172)	(0.3913)
High			
0.0108***	0.0112***	0.0087**	0.0077**
(0.0029)	(0.0029)	(0.0199)	(0.0362)

hypothesis. Panels A and B show that the media effect is stronger among stocks with low analyst coverage and a high percentage of individual ownership. These stocks are poorly covered by conventional information channels, and our results suggest that media coverage plays a large incremental role. Panels C and D show that the magnitude and significance of the media effect monotonically increase with idiosyncratic volatility and idiosyncratic volatility per shareholder, consistent with the predictions of the Merton model. The magnitude of the effect is about 1% per month among stocks with the highest measures (Panels C and D), which is economically large.

In summary, the results in the last two sections provide support for both the illiquidity hypothesis and the investor recognition hypothesis. However, although illiquidity may explain why the media effect persists, it does not explain why it arises in the first place. We conclude that the media effect may stem from media's role in enhancing investor recognition, and that a lack of adequate liquidity helps explain why it is not arbitraged away.

D. Media, Analyst Dispersion, and Idiosyncratic Volatility

An interesting question is whether the media effect is subsumed under recently documented anomalies related to analyst dispersion and idiosyncratic volatility. Diether et al. (2002) (DMS) document that stocks with high analyst forecast dispersion exhibit low future returns. Building on Miller (1977), they argue that forecast dispersion proxies for heterogeneity in investors' opinions and that under short-sales constraints, prices reflect the most optimistic views. Ang et al. (2006) document that stocks with high idiosyncratic volatility earn low future returns. This is at odds with the notion that investors should be rewarded for bearing risk that they cannot diversify away (e.g., Merton (1987)). Furthermore, this effect cannot be explained by stocks' exposure to systematic volatility, leading the authors to conclude that the finding represents a puzzle.

We first note that the main finding in this paper is directionally consistent with both results. Indeed, media coverage is positively related to both analyst dispersion and idiosyncratic volatility (Table V). Thus, our finding that high-media coverage stocks earn lower returns is consistent with high analyst dispersion stocks and high idiosyncratic volatility stocks earning lower returns.

To investigate whether the media effect is subsumed under either effect, we double-sort stocks by media coverage and either analyst dispersion or idiosyncratic volatility, and compare the return differential along each dimension. Table X reports the results. Excess returns for each group are calculated using the DGTW characteristic-based benchmark method.

Double-sorting stocks by media coverage and idiosyncratic volatility (Panel A) reveals that, controlling for idiosyncratic volatility (columns of the table), there is a large no-media premium among high idiosyncratic volatility stocks, and an insignificant premium in the other two idiosyncratic volatility groups. This is consistent with results in Table IX that the media effect is concentrated in the high idiosyncratic volatility group. Controlling for media coverage (rows of

Table X

Media Effect, Analyst Dispersion, and Idiosyncratic Volatility

This table examines whether the media effect is subsumed under the idiosyncratic volatility effect (Ang et al. (2006)) and the analyst dispersion effect (Diether, Malloy, and Scherbina (2002)). We double-sort stocks by media coverage and idiosyncratic volatility and analyst dispersion. Excess returns are computed using the DGTW characteristic-based benchmark methods. t-statistics are reported in parentheses.

Panel A: Double-Sort Media Coverage and Idiosyncratic Volatility

	Low Idiosyncratic Volatility	Medium Idiosyncratic Volatility	High Idiosyncratic Volatility	High − Low Idiosyncratic Volatility
No media	0.001	0.002	0.005	0.005
	(1.569)	(4.858)	(7.614)	(5.809)
Low media	0.002	0.001	0.003	0.001
	(3.012)	(0.404)	(1.547)	(0.435)
High media	0.001	0.002	−0.005	−0.006
	(2.215)	(1.907)	(−2.405)	(−3.713)
No − high media	0.001	0.000	0.010	
	(0.93)	(0.423)	(4.584)	

Panel B: Double-Sort Media Coverage and Analyst Dispersion

	Low Dispersion	Medium Dispersion	High Dispersion	High − Low Dispersion
No media	0.006	0.004	−0.001	−0.007
	(11.662)	(7.026)	(−0.921)	(−7.833)
Low media	0.003	0.004	−0.004	−0.007
	(3.254)	(4.006)	(−2.816)	(−4.197)
High media	0.003	0.001	−0.004	−0.006
	(3.297)	(1.219)	(−2.557)	(−4.039)
No − high media	0.004	0.003	0.003	
	(3.021)	(2.115)	(1.714)	

the table), however, shows that the "puzzle" documented by Ang et al. (2006)—that high idiosyncratic volatility stocks earn low returns—only obtains in the high media coverage subset; the puzzle disappears or reverses in the other media-coverage groups. In particular, high idiosyncratic stocks earn significantly *higher* returns than low idiosyncratic volatility stocks as suggested by Merton (1987) among no-coverage stocks.

These results first indicate that the media effect is not subsumed under the idiosyncratic volatility effect: The no-coverage premium is always either positive or insignificant, while the idiosyncratic volatility effect *reverses* among no-coverage stocks. Furthermore, the fact that among no-coverage stocks, high idiosyncratic volatility stocks earn higher returns is consistent with the notion that idiosyncratic risk should be priced (Merton (1987)). Thus, our evidence suggests that the idiosyncratic volatility puzzle may be limited to a certain subsets of stocks, for example, those with high media coverage and overall good information dissemination.

Double-sorting by media coverage and analyst dispersion (Panel B) shows that neither effect subsumes the other. Within each media coverage group, an analyst dispersion effect obtains whereby stocks with higher dispersion earn lower returns; similarly, within each analyst dispersion group, a media effect obtains whereby no-coverage stocks earn a return premium. However, the analyst dispersion effect appears considerably stronger in magnitude and significance than that in the media effect. This is perhaps not entirely surprising given that our sample consists of mainly large and liquid NYSE stocks. The incremental role played by media is probably weaker than that in smaller stocks.

V. Conclusion

We examine the relation between media coverage and the cross-section of stock returns. We find a significant return premium on stocks with no media coverage: On average, stocks not featured in the media outperform stocks frequently featured by over 0.20% per month, even after accounting for widely accepted risk factors—market, size, book-to-market, momentum, and liquidity. Moreover, this return premium is particularly large for small stocks and stocks with high individual ownership, low analyst following, and high idiosyncratic volatility. For these subsamples, stocks with no media coverage outperform those with high media coverage by 0.65–1% per month. These figures are not only statistically significant but also economically large.

We show that the media effect is robust to a number of well-known return anomalies and is distinct from time-series patterns such as return reversals and continuations. Instead, the phenomenon represents a stable cross-sectional return differential among high-coverage stocks and low-coverage stocks that could be explained by either illiquidity or investor recognition. We provide evidence that supports both hypotheses. However, since illiquidity can only explain the persistence of the phenomenon but not its cause, we conclude that the media effect stems from an information story such as Merton (1987), and the lack of liquidity helps perpetuate the phenomenon.

We also show that the media effect is consistent with, but not subsumed under, recently documented anomalies associated with analyst forecast dispersion and idiosyncratic volatility. Recent research shows that stocks with high analyst forecast dispersion and high idiosyncratic volatility earn low returns. We find that media coverage is positively related to both analyst forecast dispersion and idiosyncratic volatility. Thus, our finding that high-media coverage stocks earn lower returns is consistent with both results. Interestingly, if idiosyncratic volatility is interpreted as an indication of the speed at which firm-specific information is incorporated into prices (e.g., Durnev, Morck, and Yeung (2004)), then the positive correlation between media coverage and idiosyncratic volatility suggests that media coverage expedites the impounding of information into prices. On the other hand, the positive correlation between media coverage and analyst forecast dispersion shows that media coverage does not lead to the convergence of opinions. These observations suggest that mass media's effect on security pricing stems from its ability to disseminate information broadly, rather than to shape opinions or form consensus.

One practical implication of our results is that coverage by mass media can play a role in alleviating information problems even if it does not break genuine news. This has the further implication that companies' media relations activities can affect their cost of capital. In recent years, regulatory changes in the securities industry and cuts in Wall Street research departments have left many firms without analyst coverage. Our results suggest that the media (and firms' media relations departments) may offer a substitute or a supplement to traditional channels of corporate information such as analyst coverage.

Appendix

Table AI
Variables' Definitions

	Stock Characteristics
Amihud's (2002) illiquidity ratio	Stock's absolute return divided by its daily dollar trading volume, scaled by 10^6.
Analyst coverage	Natural log of 1 plus the number of analysts issuing earnings forecasts on the stock in the past year.
Analyst dispersion	Natural log of 1 plus the standard deviation of analyst forecasts divided by the absolute value of the mean forecast.
Bid-ask spread	Difference between the ask and the bid prices divided by the midpoint.
Book-to-market	Natural log of the book value of equity divided by the market value of equity, as of the previous year end.
Dollar trading volume	Daily value of trades in a stock, averaged over all days in a year.
Fraction of individual ownership	Percentage of the stock's shares outstanding owned by individuals.
Idiosyncratic volatility	Natural log of the residual stock return from a Fama-French (1993) three-factor regression based on daily data.
Idiosyncratic volatility per investor	Idiosyncratic volatility scaled by the number of investors obtained from 13f filings.
Past year (month) absolute return	Absolute value of past year (month) return.
Past year (month) return	(Signed) stock's return measured over the previous year (month).
Price	Average closing price during the previous month.
Size	Natural log of the average market capitalization of equity over the previous calendar year, in thousands of dollars.
	Factors
Mkt-rf	Market return minus return on the U.S. Treasury bond.
SMB	Return of a portfolio of small stocks minus the return of a portfolio of large stocks.
HML	Return on a portfolio of stocks with high book-to-market ratio, minus return on a portfolio of stocks with low book-to-market ratio.
UMD	Return on a portfolio of stocks with a high past 12-month return, minus the return on a portfolio of stocks with a low past 12-month return.
LIQ	Traded liquidity factor constructed by Pastor and Stambaugh (2003).

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