Information, Analysts, and Stock Return Comovement

Allaudeen Hameed
National University of Singapore

Randall Morck
University of Alberta

Jianfeng Shen
University of New South Wales

Bernard Yeung
National University of Singapore

Analysts follow disproportionally firms whose fundamentals correlate more with those of their industry peers. This coverage pattern supports models of profit-maximizing information intermediaries producing preferentially information valuable in pricing more stocks. We designate highly followed firms whose fundamentals best predict those of peer firms as bellwether firms. When analysts revise a bellwether firm's earning forecast, it changes the prices of other firms significantly; however, revisions for firms that are less intensely followed do not change the prices of heavily followed firms. Unidirectional information spillovers explain how the more accurately priced stocks might exhibit more comovement. (*JEL* G14)

Stocks followed by more analysts appear to be priced more accurately (Brennan, Jegadeesh, and Swaminathan 1993; Walther 1997), yet their returns are also more prone to comove (Piotroski and Roulstone 2004; Chan and Hameed 2006), which seems anomalous because a firm's stock price moves idiosyncratically as it incorporates new firm-specific information (French and Roll 1986; Roll 1988). Moreover, higher firm-specific return volatility (i.e., lower comovement)

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is linked to more intense information incorporation into stock prices (e.g., Morck, Yeung, and Yu 2000, 2013; Wurgler 2000; Durnev et al. 2003, 2004; Jin and Myers 2006).

This paper resolves the seeming anomaly by showing that stocks that are covered widely by analysts exhibit more comovement precisely because they are priced more accurately and, therefore, provide signals with which to update the prices of more opaque stocks. Thus, higher return comovement associated with more analysts following need not imply stock pricing that is less informative. Rather, it reflects spillovers as granular firm-specific information changes the prices of related stocks. Specifically, information about well-covered firms affects prices of thinly covered firms (contemporaneously and with a lag), but no opposite effect is evident.

To examine the analysts' role as information intermediaries, we derive testable propositions consistent with recent models of information intermediaries (Veldkamp 2006a). First, because information is a nonrival good, profit-maximizing analysts, incurring a fixed cost of information production, produce the information that fetches the highest price from investors. Rationally, investors value information useful for predicting many stocks more highly than information useful for predicting only one stock. Analysts therefore ought to disproportionately follow stocks whose fundamentals correlate more with those of other firms. Following financial practitioners, we dub these "bellwether firms." Second, new information about a bellwether firm should commensurately change the stock prices of other firms whose fundamentals correlate highly with those of the bellwether firm because investors use it to infer changes in their fundamentals too. This spillover should be stronger to stocks that are less followed.

Consistent with the first proposition, we find more analysts following stocks whose fundamentals are more correlated with the fundamentals of many other firms. Our findings hold after controlling for other firm characteristics found to attract analysts following, including market capitalizations, trading volumes, volatility, and institutional ownership (Bhushan 1989; Brennan and Hughes 1991; Alford and Berger 1999).

Consistent with the second proposition, we find strong evidence of information spillovers from high-analyst firms to other fundamentally related firms. From the highest tertile of analyst coverage in each industry each year, we select the firm whose fundamentals correlate most strongly with those of all other firms in the industry, and label these "industry bellwether firms." When analysts revise their earnings forecasts for bellwether firms, we observe significant effects on the current and future stock prices of their industry peers. Moreover, this effect is higher for peers with lower analyst coverage. Importantly, these information spillovers are unidirectional: earnings forecast revisions for firms that are less intensely followed do not predict the prices of heavily followed firms. Our estimates show an analyst's revision of a bellwether firm's forecasted earnings having significant cross-firm spillover for up to 1 month (in event time).

These findings complement those in Kelly and Ljungqvist (2012), who show elevated asymmetric information in the prices of other firms with correlated fundamentals following a firm's coverage terminations, as implied by Admati (1985) and Veldkamp (2006a). Following Kelly and Ljungqvist (2012) in taking as exogenous the analyst coverage terminations because of brokerage firms' closures of research departments, we show further that coverage terminations in a firm appear to cause its investors to rely more heavily on the information about bellwether firms in the industry. Specifically, we again find a one-way spillover from bellwether firms to industry peers when coverage exogenously declines for the thinly covered firms.

Further tests weigh against possible alternative explanations of these findings. The first possibility is that our results are influenced by momentum. Controlling for firm size, Hong, Lim, and Stein (2000) confirm Hong and Stein's (1999) prediction of firms with less coverage exhibiting stronger price momentum; that is, more underreaction to information and slower information diffusion (Jegadeesh and Timan 1993). Bernard and Thomas (1989) document price underreactions to earnings information. However, we show that our findings are not due to momentum effects measured using lagged stock returns, lagged own earnings information, or lagged earnings information about a portfolio of firms in the industry. Second, Lo and MacKinlay (1990) find small firms' stock returns lagging those of large firms, suggesting slow diffusion of information from large to small firms within an industry (Hou 2007). Brennan, Jegadeesh, and Swaminathan (1993) and Chan and Hameed (2006) find thinly followed stocks adjusting with a more significant lag to common market-wide information. Our findings are not subsumed by such effects. Rather, they contribute a new stylized fact to this literature: analysts' information about intensely covered firms is impounded immediately into their stock prices, but affects, with a lag, the prices of more thinly covered firms with correlated fundamentals.[1]

Our findings are highly robust. A broad range of plausible alternative econometric approaches yields results qualitatively similar to those in the tables, by which we mean comparable patterns of signs, significance, and rough point estimates. Other data also support our main findings: we find that institutional investors buy low- and zero-coverage firms with correlated fundamentals upon upward revisions to a bellwether firm's earnings forecast.

We believe that Ockham's razor favors our conclusion that investors use information supplied by analysts about bellwether stocks to value relatively neglected stocks, inducing comovement in their stock returns. These results

[1] Related work posits other reasons for such lags. Menzly and Ozbas (2010) highlight lagged information transfer between firms in related product markets, and Cohen and Lou (2012) link longer delays in stock prices incorporating common industry information to greater firm diversification.

thus validate key empirical implications of the information intermediation theories (Veldkamp 2006a, 2006b). In addition, because prior work on analysts' earnings forecasts focuses on the forecast firm's own stock price (e.g., Stickel 1991; Park and Stice 2000; Cooper, Day, and Lewis 2001; Clement and Tse 2003; Gleason and Lee 2003), our findings open new empirical territory in further exploring the price reactions of other stocks to bellwether stock earnings forecast revisions, as well as in better identifying bellwether stocks themselves. Finally, our findings justify academic research into the finance industry practice of designating "bellwether" stocks as barometers of sectoral trends; as, for example, when analysts use information about Wal-Mart to infer fundamental values of other retailers.

1. Information Markets and Return Comovement

Veldkamp (2006a) models profit-maximizing intermediaries selling investors information produced with a fixed-cost technology and an increasing return to scale. As information is costly to discover but cheap to replicate, investor demand is higher for information about firms whose fundamentals help price not only their own stocks but also the stocks of related firms. Firm-level information intermediaries, such as financial analysts, supplying information of the highest total value, thus follow bellwether firms, whose fundamentals best predict those of many other firms. Investors, using this information to price other stocks, about which information is less readily available, cause their prices to move with that of the relevant bellwether firm. Bellwether stocks thus comove more with other stocks but are the most accurately priced nonetheless.

Consistent with this market for information framework, analyst coverage correlates with various firm characteristics. Bhushan (1989) finds analyst coverage increasing in firm size, consistent with information about larger firms being more valuable, perhaps because larger trades are possible without moving the stock price greatly. Brennan and Hughes (1991) and Alford and Berger (1999) find more analysts following more heavily traded firms, perhaps because higher turnover generates more brokerage commissions. Bhushan (1989) also finds more volatile stocks followed by more analysts, perhaps because information predicting larger price jumps yields larger arbitrage profits. Higher information production costs could explain why Bhushan (1989) finds fewer analysts following firms with more lines of business. Higher information demand might explain why more analysts follow firms with higher institutional ownership (Bhushan 1989; O'Brien and Bhushan 1990), which leads to the following proposition.

Proposition 1: Firms whose fundamentals better predict the fundamentals of other firms in their industries attract more analyst coverage, controlling for other factors affecting coverage such as firm size, trading volume, return volatility, firm diversification, and institutional ownership.

This proposition implies a bellwether-firm effect. Because we define a *bellwether firm* as a firm that is intensely followed by analysts and whose fundamentals best predict the prices of other firms in its industry, consequently, firm-specific information about bellwether firms should move the prices of other related firms, reflecting information spillovers as comovement. We operationalize this prediction by examining the price effect of analysts' earnings forecast revisions about a bellwether firm on other firms in its industry, especially those followed by few or no analysts, which leads to the next proposition.

Proposition 2: Analysts' earnings forecast revisions of bellwether firms influence the returns of other firms with related fundamentals, but for which information is scarcer.

2. Fundamental Correlations and Analyst Coverage: Data and Analyses

2.1 Sample selection

Our sample contains all common stocks (share code 10 or 11) listed on New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ Stock Market (NASDAQ), requiring nonmissing data in both The Center for Research in Security Prices (CRSP) and COMPUSTAT for the period 1984 to 2011. We require the average daily stock price in December of the previous year to be above \$1, to minimize market frictions, such as price discreteness and bid-ask effects, associated with penny stocks. We merge stock price and earnings data in CRSP-COMPUSTAT with analyst coverage data in the Institutional Brokers' Estimate System (I/B/E/S). Finally, we merge the result with quarterly institutional holdings data in Thomson Reuters' Institutional Holdings (13F) database. Our final sample includes 138,633 firm-years averaging 4,951 firms per year. Annual cross-sections start with 4,283 firms in the CRSP-COMPUSTAT merged sample in 1984, grow steadily to peak at 6,813 firms in 1998, and then decrease gradually to 3,642 firms in 2011.

2.2 Firm-specific variables

2.2.1 Analyst coverage (*ANALYST*). Analyst coverage, *ANALYST*, is the number of analysts making 1-year-ahead earnings (EPS) forecasts each firm-year.[2] Firms not covered by I/B/E/S are assumed to have zero analyst coverage.[3] In an average year, 1,611 firms (almost one third

[2] The results reported in the paper are based on the number of estimates in the consensus forecasts in December of each year. Our results are unaffected if we measure a firm's analyst coverage as the number of unique analysts making 1-year-ahead earnings forecasts or the average monthly number of estimates used to construct the consensus earnings forecasts during the year.

[3] Our classification of firms with zero coverage is subject to the caveat that we are excluding coverage not reported in I/B/E/S. However, this is likely to understate the evidence of spillover.

of all firms in the CRSP-COMPUSTAT-merged sample) lack analyst coverage.

2.2.2 Partial correlation in fundamentals (PCORR_ROA). The Veldkamp (2006a) model suggests analyst following and information spillover are likely larger for stocks whose fundamentals correlate more with those of many other firms. Changes in firm-specific fundamentals are typically inferred from accounting measures, such as return on assets (*ROA*) or return on sales (*ROS*) (Morck, Yeung, and Yu 2000; Piotroski and Roulstone 2004; Durnev et al. 2004; Wei and Zhang 2006; Chun et al. 2008). Although *ROA* and *ROS* are noisy measures of fundamental values, their historical correlations are nonetheless viable proxies for the correlations in fundamentals.

Changes in firms' fundamental values reflect common shocks to industries: shifts in demand or supply, technological change, regulatory shocks, and other things that affect entire industries. Therefore, we begin our analysis with estimates of each firm's contribution to fundamental comovement of other peer firms within its primary industry. We use a three-step procedure to construct our measure of fundamental correlations for firm k, each year. We first run a market model of *ROA*s for each firm in the industry, other than firm k, using quarterly data over a 5-year window,

$$ROA_{iq} = a_i + b_i ROA_{Mq} + e_{iq}, \tag{1}$$

where ROA_{iq} is firm i's ROA earnings before extraordinary item (Compustat item 8) over total assets (item 44) in quarter q, and ROA_{Mq} is the asset-weighted ROA for the market portfolio, excluding firm$k$, in the same quarter. The regression R^2 of Equation (1), $R^2_{i,excl.k}$, is the fraction of variation in firm i's *ROA*s explained by the market.

The second step reruns the regression in Equation (1), but includes firm k's return on assets, ROA_{kq}, as well,

$$ROA_{iq} = a_i + b_i ROA_{Mq} + c_i ROA_{kq} + e_{iq}. \tag{2}$$

This regression's R^2 is denoted $R^2_{i,incl.k}$. For each pair of stocks (k,i) in the industry, $R^2_{i,incl.k} - R^2_{i,excl.k}$ is the partial contribution of firm k in explaining firm i's fundamentals, controlling for market-wide common fundamental variations. We then calculate a partial correlation coefficient equal to this difference in R^2s normalized by the unexplained fraction of variation in Equation (1).

$$PCORR\_ROA_{k,i} = (R^2_{i,incl.k} - R^2_{i,excl.k})/(1 - R^2_{i,excl.k}). \tag{3}$$

Defining N_I as the number of firms in industry I, this procedure generates $(N_I - 1)$ pairwise partial correlation coefficients as in Equation (3). We define industries using the 48 Fama and French (1997) industry classifications, and require at least12 nonmissing quarterly observations in the 5-year estimation window of Equation (1) and (2).

The third step generates an estimate of firm k's overall fundamentals correlation with all other firms in its industry. We average $PCORR\_ROA_{k,i}$ across all firms $i(i \neq k)$ in the industry, denoting this $PCORR\_ROA_k$. Because $PCORR\_ROA_k \in [0, 1]$, a logit transformation produces a roughly normally distributed measure of the partial correlation of firm k's fundamentals with those of its industry peers,

$$LPCORR\_ROA_k = Ln[PCORR\_ROA_k/(1-PCORR\_ROA_k)]. \quad (4)$$

Repeating these three steps for each firm, each year generates a firm-year panel of $LPCORR\_ROA_{k,t}$. A higher $LPCORR\_ROA_{k,t}$ means firm k's *ROA*s contribute more toward explaining variation in the *ROAs* of other firms in the industry, after controlling for common market-related variation.

2.2.3 Other firm-level variables. We require controls for firm characteristics shown to be important in prior work on return comovement and analyst coverage (e.g., Bhushan 1989; Piotroski and Roulstone 2004; Chan and Hameed 2006; Frankel, Kothari, and Weber 2006). These variables, measured annually, include firm size (*SIZE*), mean daily stock turnover (*TURNOVER*), standard deviation of daily stock returns (*STDRET*), fraction of the shares held by institutional investors (*IO*), and industry focus measured by a Herfindahl index of sales across the firm's 2-digit SIC-code industry segments (*HERF_SALES*).

2.3 Summary statistics

Panel A in Table 1 reports descriptive statistics for key variables.[4] The average number of analysts covering a firm (*ANALYST*) in any year is 4.6, and the median is 2, indicating a positively skewed distribution of coverage. The partial correlation in ROA, *PCORR_ROA*, averages 11.68%, and varies substantially across firms: its standard deviation is 5.94%. The industry focus variable, *HERF_SALES*, shows over half the firms operating in only one industry, consistent with Piotroski and Roulstone (2004), and others.

Table 1, Panel B, summarizes the characteristics of firms by analyst coverage. Within each industry, covered stocks are sorted into three equal groups based on *ANALYST* (*high*, *medium*, and *low*), and uncovered stocks form a fourth group (*zero*).[5] Panel B shows the average high-*ANALYST* firm followed by about 14 analysts on average, whereas the low group averages to 1.67. For each analyst group, the panel reports average firm characteristics from

[4] All variables are winsorized at the upper and bottom one percentile values each year, except for *ANALYST* and *IO*, which are winsorized at its upper one percentile value only. Unwinsorized variables generate results qualitatively similar to the tables, suggesting that our results are robust to extreme values.

[5] To be included in the analysis, we also require that at least nine firms be covered by analyst in each industry-year.

Table 1
Summary statistics

Panel A: Summary statistics

Variable	Mean	Std.	Q1	Median	Q3
ANALYST	4.603	6.354	0	2	6
PCORR_ROA (%)	11.679	5.941	7.711	10.227	13.842
SIZE ($ millions)	1209.801	4414.930	31.532	119.552	557.831
TURNOVER (%)	0.517	0.610	0.144	0.307	0.648
HERF_SALES	0.857	0.235	0.715	1	1
STDRET (%)	3.571	2.038	2.089	3.077	4.526
IO (%)	33.810	28.169	9.054	27.395	54.666

Panel B: Summary statistics by analyst coverage groups

	Analyst coverage group				T-test	
Variable	Zero	Low	Medium	High	High–zero	High–low
ANALYST	0	1.669	4.891	13.978		
PCORR_ROA (%)	10.663	12.026	12.128	11.994	*4.33*	*−0.05*
SIZE ($millions)	68.317	197.884	621.883	4502.574	*13.45*	*13.22*
TURNOVER (%)	0.296	0.453	0.625	0.777	*8.59*	*7.20*
HERF_SALES	0.899	0.873	0.846	0.792	*−7.70*	*−6.82*
STDRET (%)	4.331	3.825	3.187	2.662	*−11.57*	*−13.09*
IO (%)	12.084	29.169	44.949	58.710	*37.84*	*27.66*

Panel C: Average yearly correlation coefficients

Variable	*LPCORR_ROA*	*Ln(SIZE)*	*TURNOVER*	*HERF_SALES*	*Ln(STDRET)*	*Ln(IO)*
Ln(1+ANALYST)	0.110***	0.818***	0.306***	−0.189***	−0.362***	0.655***
LPCORR_ROA		0.097***	0.008	0.052***	−0.124***	0.049***
Ln(SIZE)			0.213***	−0.270***	−0.507***	0.646***
TURNOVER				0.047	0.259***	0.253***
HERF_SALES					0.176***	−0.212***
Ln(STDRET)						−0.347***

In Table 1, we present the summary statistics of firmspecific variables, computed each year. *ANALYST* is the number of analysts covering the firm; *SIZE* is the firm's market capitalization; *TURNOVER* is the average of daily share turnover; *HERF_SALES* is the Herfindahl index of sales across 2-digit SIC business segments; *STDRET* is the standard deviation of daily returns; and *IO* is the fraction of shares outstanding held by institutional investors. *PCORR_ROA* measures the partial correlation of each firm earnings (return on assets. *ROA*) with earnings of other firms in the same industry. In Panel A, we report the mean, median, standard deviation and the first (Q1) and third (Q3) quartile values of these variables. In Panel B, the averages are reported for stocks sorted by analyst coverage within each industry each year into four groups: zero, low, medium and high coverage. The last two columns report the robust t-statistics (clustered by industry) for the tests of equality of between high and low (or zero) analyst groups. Panel C reports the average correlation coefficients between the variables, where the prefix *Ln* denotes logarithmic values of the variables and *LPCORR_ROA* is the logit transformation of *PCORR_ROA*. *, **, and *** indicate that the average correlation coefficient is statistically significant at 10%, 5%, and 1% levels respectively based on *HAC* standard errors.

the prior year. Unsurprisingly, high-*ANALYST* firms have the largest market capitalizations, institutional ownership, and trading activity. They also have returns that are less volatile compared with either zero- or low-*ANALYST* firms. The group means of *PCORR_ROA* reveals high-*ANALYST* firms' *ROA*s to be more correlated with the *ROA*s of other firms in their industries than are zero-*ANALYST* firms' *ROA*s. However, the *PCORR_ROA* of high-*ANALYST* firms differs insignificantly from that of low-*ANALYST* firms. Panel C shows many firm characteristics, especially *ANALYST*, to correlate with firm size, thus the univariate statistics in Panel B are clearly dependent. Therefore, we turn to multivariate analysis.

2.4 Regression results

Proposition 1 in Section 1 motivates regressions of analyst coverage of each firm k each year t of the form

$$\begin{aligned}Ln(1+ANALYST_{k,t}) = a + a_1 LPCORR\_ROA_{k,t-1} + a_2 Ln(SIZE_{k,t-1}) \\ + a_3 TURNOVER_{k,t-1} + a_4 HERF\_SALES_{k,t-1} \\ + a_5 Ln(STDRET_{k,t-1}) + a_6 Ln(IO_{k,t-1}) \\ + \Sigma c_I INDDUM_{I,k,t} + \Sigma dy\, YEARDUM_{y,k,t} + e_{k,t}. \quad (5)\end{aligned}$$

Equation (5) controls for the firm-specific variables in Section 2.3, as well as industry and year fixed effects, *INDDUM* and *YEARDUM*.[6] We estimate Equation (5) as a panel regression on the full 1984–2011 sample and on four 7-year subperiods: 1984–1990, 1991–1997, 1998–2004, and 2005–2011. All t-statistics use robust standard errors clustered by industry (Petersen 2009).[7]

In Table 2, we summarize these regressions, showing more analysts following larger (*SIZE*), and more heavily traded (*TURNOVER*), focused (*HERF_SALES*), eventful (*STDRET*), and institutionally owned (*IO*) firms. These findings affirm those of Piotroski and Roulstone (2004) and Chan and Hameed (2006) on the determinants of analyst following. More importantly, consistent with proposition 1, the table shows *LPCORR_ROA* attracting a positive coefficient in all subperiods, and attaining statistical significance in the full sample period and in three of the four subperiods. These results support the hypothesis that more analysts follow firms whose fundamentals more plausibly help price many other firms.

Further, the findings are highly robust, in that various alternative approaches yield qualitatively similar results. In particular, if lagged analyst coverage, $Ln(1{+}ANALYST_{k,t-1})$, is included to control for persistence in analyst coverage and any dependence of analyst coverage on unobserved time-invariant firm characteristics, the coefficient of *LPCORR_ROA* remains positive and significant in the full sample and in the last three subperiods. *LPCORR_ROA* also attracts a positive coefficient in annual cross-sectional regressions every year from 1984 to 2011, except 1987 and 1988, and the mean of these coefficients, 0.047, is highly significant (*HAC* t-stat = 4.28). The results are qualitatively unchanged if *ROA* is replaced with *ROS*) or if *ROA* is redefined as operating income after depreciation and amortization over total assets. Nonlinear firm-size effects, either including *SIZE* and its square or replacing *SIZE* by size decile dummies, preserve the significant positive coefficient of *LPCORR_ROA* in Equation (5). Finally, estimating *LPCORR_ROA* by

6 We add 1% to *IO* when taking the logarithmic transformation to deal with zero *IO*.

7 We cluster standard errors by industry because the key variable of interest, *LPCORR_ROA*, is measured within each industry. A two-way clustering of standard errors by firm and year yields larger t-statistics in most cases, especially for *LPCORR_ROA*.

Table 2
Determinants of analyst coverage

	Sample period				
Independent variables	1984–2011	1984–1990	1991–1997	1998–2004	2005–2011
$LPCORR\_ROA_{k,t-1}$	0.058	0.014	0.052	0.057	0.074
	4.35	*0.41*	*2.30*	*3.06*	*5.94*
$Ln(SIZE_{k,t-1})$	0.397	0.454	0.431	0.378	0.361
	61.55	*33.99*	*37.96*	*65.69*	*51.66*
$TURNOVER_{k,t-1}$	0.158	0.343	0.225	0.167	0.164
	12.37	*5.42*	*8.64*	*9.41*	*11.02*
$HERF\_SALES_{k,t-1}$	0.142	0.194	0.169	0.065	0.152
	6.16	*3.20*	*3.69*	*1.91*	*4.44*
$Ln(STDRET_{k,t-1})$	0.044	0.045	0.045	0.097	−0.008
	2.39	*1.81*	*1.62*	*4.54*	*−0.35*
$Ln(IO_{k,t-1})$	0.132	0.142	0.096	0.102	0.151
	11.94	*9.03*	*5.88*	*10.52*	*13.83*
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R-squared	0.691	0.725	0.731	0.680	0.662

In Table 2, we present the determinants of analyst coverage estimated using the following panel regression:

$$Ln(1+ANALYST_{k,t}) = a + a_1 LPCORR\_ROA_{k,t-1} + a_2 Ln(SIZE_{k,t-1}) + a_3 TURNOVER_{k,t-1}$$
$$+ a_4 HERF\_SALES_{k,t-1} + a_5 Ln(STDRET_{k,t-1}) + a_6 Ln(IO_{k,t-1}) + \Sigma c_I INDDUM_{I,k,t}$$
$$+ \Sigma dy\, YEARDUM_{y,k,t} + e_{k,t},$$

where, for each firm k and year t, *ANALYST* is the number of analysts covering the firm; *LPCORR_ROA* is the logit transformation of the partial correlation measure of *ROA*; *SIZE* is market capitalization; *TURNOVER* is the average of daily share turnover; *HERF_SALES* is the Herfindahl index of sales across 2-digit SIC business segments; *STDRET* is the standard deviation of daily returns; *IO* is the fraction of shares outstanding held by institutional investors; *INDDUM*s are industry dummies; and *YEARDUM*s are year dummies. The robust t-statistics clustered by industry are provided in *italics*.

classifying firms into industries using five-digit Global Industry Classification Standard codes also yields qualitatively similar results.

Overall, these findings are consistent with more analysts choosing to follow firms whose fundamentals are useful in predicting the values of other firms, as Veldkamp (2006a) predicts.

3. Bellwether Firms

Proposition 2, in Section 1, argues that investors use information about heavily covered stocks to price stocks followed by few or no analysts, thereby generating comovement in stock returns (Veldkamp 2006a). We use stock-price reactions to revisions in analysts' earnings forecasts to infer information spillovers. If investors use information generated by analysts about a prominent stock to price relatively neglected stocks, revisions in forecasted earnings of the prominent stock should affect the prices of fundamentally related firms that are less followed, whereas earnings forecast revisions for stocks that are less prominent should be less important in pricing other stocks.

Drawing from Section 2, we identify a prominent stock in each industry each year and designate it a *bellwether stock*. More precisely, each year,

Table 3
Summary statistics of bellwether firms

Variable	Mean	Std.	Q1	Median	Q3
ANALYST	13.700	6.643	9	12	18
PCORR_ROA (%)	19.077	6.248	14.897	18.048	22.022
SIZE ($millions)	4041.401	7562.544	530.872	1424.519	3705.875
TURNOVER (%)	0.720	0.716	0.254	0.473	0.891
HERF_SALES	0.760	0.277	0.501	0.958	1
STDRET (%)	2.533	1.233	1.709	2.235	2.932
IO (%)	60.279	22.486	44.801	59.953	76.807

In Table 3, we present the summary statistics of firm-specific variables, computed each year, for the sample of industry bellwether firms. *ANALYST* is the number of analysts covering the firm; *SIZE* is the firm's market capitalization; *TURNOVER* is the average of daily share turnover; *HERF_SALES* is the Herfindahl index of sales across 2-digit SIC business segments; *STDRET* is the standard deviation of daily returns; and *IO* is the fraction of shares outstanding held by institutional investors. *PCORR_ROA* measures the partial correlation of each firm earnings (returns on assets or *ROA*) with earnings of other firms in the same industry. We report the mean, median, standard deviation and the first (Q1) and third (Q3) quartile values of these variables.

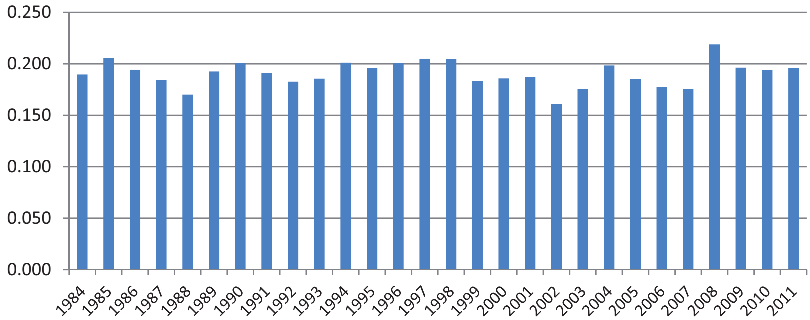

Figure 1
Average *PCORR_ROA* of bellwether firms by year
Figure 1 shows the yearly average value of *PCORR_ROA* of bellwether firms, the partial correlation of bellwether firms' earnings (returns on assets or *ROA*) with earnings of other firms in the same industry.

each industry's bellwether stock is the one that is in the industry's top tertile by analyst coverage (*ANALYST*) and, within the top coverage tertile, has the largest partial correlations in fundamentals with other stocks in the industry (*PCORR_ROA*). This admittedly simple designation criterion is readily replicable and intuitively justifiable in combining the criterion of intense analyst following and fundamentals most reflective of those of many other firms in the industry. We welcome additional work to hone these criteria.

In Table 3, we summarize the characteristics of bellwether firms. By construction, bellwether firms have both high *PCORR_ROA* and analyst following. Unsurprisingly, they are also larger, with higher institutional ownership, and are more actively traded. Their characteristics are also comparable to those of the firms with high coverage in Table 1. In Figure 1, the annual average bellwether-firm *PCORR_ROAs* from 1984 to 2011 are graphed. The grand mean of 19% balances variation from just over 16% in 2002 to almost 22% in 2008. In Figure 2, the average bellwether firm's *PCORR_ROA*

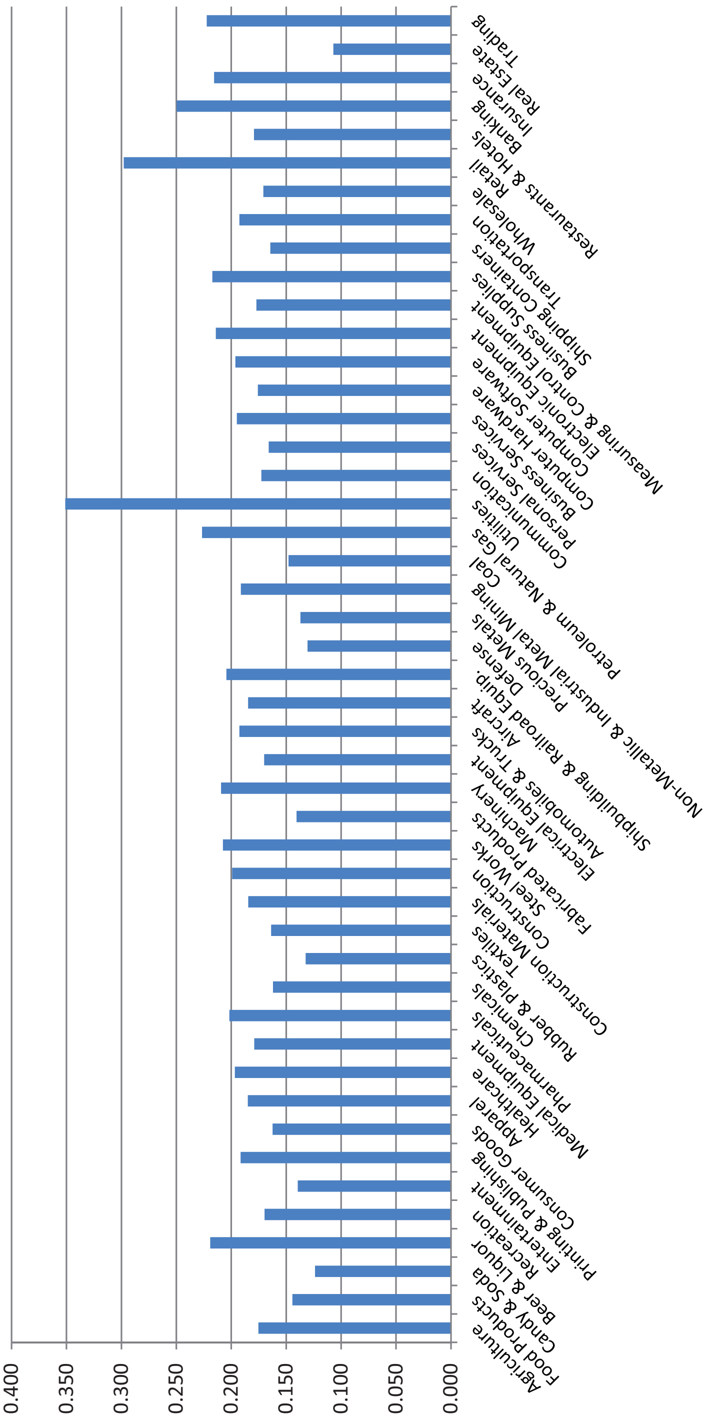

Figure 2
Average *PCORR_ROA* of bellwether firms by industry
Figure 2 shows, for each industry, the average value of *PCORR_ROA* of bellwether firms, the partial correlation of bellwether firms' earnings (returns on assets or *ROA*) with earnings of other firms in the same industry.

over every year in each industry is charted. Bellwether firms best explain other firms fundamentals in utilities (mean *PCORR_ROA* = 35.11 %), and do almost as well in retailing (mean *PCORR_ROA* = 29.79%).

3.1 Information spillover effects

Our first test examines stock-price reactions of industry-peer firms to monthly revisions in analysts' consensus earnings forecasts for the industry bellwether firm reported in I/B/E/S. The earnings forecast revision for firm k in month t, $FR_{k,t}$, is the change in the mean forecast of 1-year ahead earnings per share from month *t-1*, scaled by firm k's stock price at the end of *t-1*. Denoting the consensus earnings forecast revision for industry I's bellwether firm as $FR_{IBW,t}$, we gauge its influence on the return on industry-peer firm k, $R_{k,t}$, using panel regressions of the form:

$$\begin{aligned} R_{k,t} = {} & a_0 + b_1 FR_{IBW,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} \\ & + d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + e_{k,t}, \end{aligned} \tag{6}$$

where k indexes all firms save the bellwether firm. All monthly variables are measured at the midpoint of each month (the Thursday preceding the third Friday of the month) to align with I/B/E/S consensus earnings forecast dates.

The regressions include several controls. First, following Fama and French (1992), Daniel and Titman (1997), and Gervais, Kaniel, and Mingelgrin (2001), we control for firm characteristics shown to predict stock returns. These include the log of firm k's market capitalization at the end of month $t-1$, $ln(SIZE_{k,t-1})$; the log of its book-to-market equity ratio, $ln(BM_{k,t-1})$[8] ; and its average daily share turnover in month $t-1$, $TURNOVER_{k,t-1}$. As Table 3 shows, bellwether firms tend to be bigger and have high trading volume, so we must control for any predictive effects resulting from these firm characteristics.

Stock returns exhibit medium-term price momentum (Jegadeesh and Timan 1993), which Hong and Stein (1999) model as firm-specific information diffusing slowly across investors. Hong, Lim, and Stein (2000) present evidence consistent with this model and, controlling for firm size, find the momentum effect strongest for stocks with low analyst coverage. Additionally, stocks also underreact to information in both firm-specific earnings and analysts' earnings forecasts (Bernard and Thomas 1989; Chan, Jegadeesh, and Lakonishok 1996). We account for momentum effects by including two firm-specific variables in Equation (6): the stock's own lagged return over the 6 months from $t-2$ to $t-7$, $R_{k,t-2:t-7}$, to capture price momentum; and the stock's own consensus earnings forecast revision, $FR_{k,t-1}$, to capture earnings momentum (see also Gleason and Lee 2003).

[8] We follow Fama and French (1992) to measure book-to-market equity ratio and allow a minimum of 6-month gap between the end of the fiscal year and the return date.

Lo and MacKinlay (1990) find a lead-lag relation between the short-term returns of large and small firms. Returns on small firms appear to react to common information previously impounded in the prices of large firms. Hou (2007) finds this effect stronger within industries, suggesting the gradual diffusion of industry-wide information from larger to smaller firms. We control for the lagged incorporation of market-wide information into stock prices in the baseline Equation (6), by including the monthly CRSP value-weighted market portfolio return in months t and $t-1$, $R_{m,t}$, and $R_{m,t-1}$. Finally, we include the stock's own lagged return for the previous month, $R_{k,t-1}$, to account for short-term reversals (Jegadeesh 1990), which are related to stock illiquidity (Avramov, Chordia, and Goyal 2006).

In Table 4, we report regression coefficients and robust $t-$statistics clustered by industry.[9] Because $FR_{k,t-1}$ may correlate with the firm-specific control variables, especially $R_{k,t-1}$ and $R_{k,t-2,t-7}$, we also report estimates of Equation (6), omitting $FR_{k,t-1}$. The *All firms* column in Panel A, reporting Equation (6) estimated over the full sample of firms, confirms that the control variables capture significant predictable variation in stock returns. Consistent with prior work, significant short-term price reversals, and medium-term price momentum are evident; high-turnover and value firms earn larger returns; and stocks react to market-wide returns with a lag.

Controlling for these effects, in Table 4 we show that when analysts revise upward their earnings forecasts of bellwether firms, FR_{IBW}, a significant positive reaction is evident in the subsequent returns of other firms in the industry. The first column in Panel A shows a 1% increase in a bellwether firm's forecasted EPS predicting a 0.1% higher monthly return on other industry peers.

Panel A also presents the results of regression in Equation (6) for zero-, low-, medium-, and high-coverage groups, where firms are sorted into different groups within each industry, each year, based on the number of analysts following during the previous year. The predictive effect of the control variables is highest for uncovered firms and monotonically declines with increasing analyst coverage. The asymmetric price response across firms is marked: the effect of FR_{IBW} is strongest on the future returns on uncovered firms, and it decreases monotonically as we move to firms with more coverage. A 1% increase in FR_{IBW} anticipates a significant 0.18% higher return in uncovered firms and a 0.15% higher return in low-analyst firms. The bellwether effect drops rapidly for firms with higher coverage, anticipating a smaller 0.06% price rise for firms with medium coverage and an insignificant effect for firms in the highest-coverage group. All of these analyses exclude the bellwether firm itself, of course.

[9] Two-dimensional clustering of standard errors by firm and by month yields qualitatively similar results. For example, the coefficient on $FR_{IBW,t-1}$ is statistically significant at the 5% level in regressions for the zero- and low-analyst groups, but it is insignificant (t <1) for the medium- and high-analyst groups.

Table 4
Impact of lagged earnings forecast revisions of bellwether firms on industry stock returns

Panel A: Regression of monthly stock returns on the lagged forecast revision of the bellwether firm

	Analyst coverage groups				
Independent variables	*All firms*	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
Intercept	−1.305	−0.972	−1.580	−2.017	−1.641
	−5.26	*−4.93*	*−4.44*	*−4.03*	*−3.91*
$FR_{IBW,t-1}$	0.094	0.182	0.147	0.063	−0.022
	3.01	*4.36*	*3.54*	*1.66*	*−0.54*
$R_{k,t-1}$	−0.017	−0.021	−0.018	−0.013	−0.002
	−5.56	*−5.84*	*−5.21*	*−2.69*	*−0.36*
$R_{k,t-2,t-7}$	0.004	0.006	0.004	0.003	0.001
	3.52	*4.48*	*2.46*	*2.49*	*0.82*
$Ln(SIZE_{k.t-1})$	0.037	0.126	0.104	0.055	0.007
	1.29	*2.89*	*1.63*	*1.27*	*0.30*
$Ln(BM_{k,t,-1})$	0.513	0.827	0.467	0.328	0.113
	11.41	*13.50*	*6.05*	*9.15*	*3.15*
$TURNOVER_{k,t-1}$	0.004	−0.017	0.004	0.006	0.005
	1.38	*−3.24*	*0.79*	*1.66*	*1.78*
$Ln(IO_{k,t-1})$	*0.319*	*0.216*	*0.288*	*0.420*	*0.369*
	4.45	*2.85*	*3.22*	*4.00*	*4.13*
$R_{m,t}$	1.087	0.876	1.090	1.206	1.207
	4.34	*5.07*	*7.85*	*9.14*	*9.52*
$R_{m,t-1}$	0.190	0.298	0.263	0.146	0.030
	2.88	*5.70*	*5.86*	*3.57*	*0.99*
Rsq	0.124	0.074	0.118	0.162	0.203

Panel B: Regression of monthly stock returns on the lagged earnings forecast revision of the bellwether firm and firm k

$FR_{IBW,t-1}$	0.087	0.182	0.137	0.053	−0.024
	2.69	*4.36*	*2.97*	*1.41*	*−0.59*
$FR_{k,t-1}$	0.100		0.128	0.114	0.037
	4.81		*3.84*	*4.26*	*0.82*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.124	0.074	0.118	0.162	0.203

Panel C: Regression of monthly stock returns on the lagged earnings forecast revisions of the bellwether firm, the nonbellwether firm, and firm k

$FR_{IBW,t-1}$	0.090	0.178	0.141	0.059	−0.026
	2.58	*4.14*	*2.77*	*1.42*	*−0.67*
$FR_{INBW,t-1}$	−0.022	0.087	−0.054	−0.088	−0.007
	−0.25	*1.09*	*−0.43*	*−0.93*	*−0.09*
$FR_{k,t-1}$	0.104		0.127	0.115	0.057
	4.79		*3.85*	*4.36*	*1.07*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.124	0.074	0.118	0.162	0.202

In Table 4, Panel A we present the estimates of the following panel regression:

$$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7}$$

$$+ d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms k, excluding the industry bellwether firms. $R_{k,t}$ is firm k's stock return in month t. FR_{IBW} is the revision in consensus earnings forecasts for industry bellwether firms (i.e. same industry as firm k). R_m is the value-weighted returns of all stocks in CRSP. The firm-specific independent variables include $R_{k,t-2,t-7}$, the cumulative return over the period month $t-7$ to month $t-2$; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The coefficients for the control variables are reported in Panel A only. The robust t-statistics clustered by industry are provided in *italics*.

In Panel B, we add $FR_{k,t-1}$, the revision in consensus earnings forecasts for firm k. In Panel C, we also add $FR_{INBW,t-1}$, the revisions in consensus earnings forecasts for a nonbellwether firm in the same industry as firm k, defined as the stock with lowest *PCORR_ROA* among stocks with high analyst coverage.

Additionally, in Table 4, Panel B, we report the results of regression in Equation (6), further including the firm's own forecast revision in the previous month, $FR_{k,t-1}$. To conserve space and focus on the marginal effects of forecast revisions, the panel suppresses coefficients of the controls. The coefficients on the controls differ little from those in Panel A, though that on $R_{k,t-2,t-7}$ becomes insignificant, consistent with Chordia and Shivakumar (2006), who report price momentum subsumed by earnings momentum. Panel B shows significant lagged adjustment to the firm's own forecast revisions for low- and medium-coverage firms, but not for high-coverage firms. More importantly, accounting for FR_k does not change the coefficient on FR_{IBW}: the bellwether firm's forecast revision contains value-relevant information for other firms in the industry, above and beyond information from analysts covering those other firms.

To benchmark the spillover effects, we look for similar effects for nonbellwether firms. In each industry each year, we select the firm with the lowest *LPCORR_ROA* among firms in the highest analyst tertile in each industry as a *nonbellwether firm.* We denote its consensus earnings forecast revision in month t as $FR_{INBW,t}$.[10] Panel C of Table 4 associates FR_{INBW} with insignificant stock-price responses in other firms in the industry, regardless of the analyst group used. In contrast, the coefficient on FR_{IBW} is virtually unchanged and significant in regressions using the zero- and low-analyst groups.

These findings support a strong positive information spillover from information-laden bellwether firms to other firms in the industry, especially to information-sparse firms. Moreover, this information spillover is unidirectional, from bellwether firms to neglected firms, but not the other way. These findings also complement the within-industry transmission of information documented in Hou (2007), and might be a possible mechanism for that transmission.

If information about bellwether firms moves the prices of other related firms, earnings forecast revisions of bellwether firms should also trigger contemporaneous responses in the prices of other firms in the industry, especially firms for which less information is available. We modify the specification in Equation (6) to examine the influence of contemporaneous consensus earnings forecast revisions of bellwether firms:

$$R_{k,t} = a_0 + b_1 FR_{IBW,t} + b_2 FR_{k,t} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + e_{k,t}, \quad (7)$$

where we control for stock k's own contemporaneous earnings forecast revision, $FR_{k,t}$, as well as other variables defined in Equation (6). The estimate of Equation (7) is reported in Panel A of Table 5. The column "*All firms*" in

[10] We find qualitatively similar results if the nonbellwether firm is chosen from the middle or lowest analyst coverage tertiles.

Panel A shows a significantly positive coefficient for $FR_{IBW,t}$ explaining contemporaneous returns of all stocks in the same industry, beyond the effect of revisions in the firm's own contemporaneous earnings forecast, $FR_{k,t}$. The effect of FR_{IBW} is largest on the contemporaneous returns of uncovered firms, and it declines monotonically as analyst coverage increases. Interestingly, information about bellwether firms has an insignificant influence on other firms with high coverage. The prices of the information-laden firms are driven primarily by their own earnings information. Unsurprisingly, Panel B of Table 5 shows that further including lagged forecast revisions, $FR_{IBW,t-1}$ and $FR_{k,t-1}$, in Equation (7) leaves the contemporaneous forecast revisions dominant. Nevertheless, $FR_{IBW,t-1}$ remains significant in explaining next period's returns on uncovered firms. A similar picture emerges for the cumulative effect of $FR_{IBW,t}$ and $FR_{IBW,t-1}$ on returns: a 1% increase in the forecasted earnings of the bellwether firm is associated with a cumulative 0.37% (0.31%) monthly return in uncovered (low-coverage) firms.

Overall, Tables 4 and 5 support our main hypothesis that information generated by analysts about prominent firms moves the prices of other less information-laden firms, generating comovement in stock returns. Using contemporaneous earnings forecast revisions for bellwether firms suggests a stronger information spillover, but this result raises the issue of reverse causality: Could analysts revise their earnings forecasts of bellwether firms after observing price changes of all other firms in the industry. Tables 4 and 5 provide a ready response to this concern: the spillover effect is larger for firms covered by fewer or no analysts. Any reverse-causality argument must explain analysts relying more on the returns of relatively neglected firms to update their forecasts of bellwether firms' earnings. Although we cannot categorically exclude this potential explanation, such a reverse causality would imply a major gap in our understanding of analyst behavior. Ockham's razor favors the simpler explanation of information spilling over from bellwether firms to firms that are less covered.

3.2 Evidence from an exogenous decrease in analyst coverage

Kelly and Ljungqvist (2012) convincingly argue that a brokerage firm closing its research department is an exogenous event for the firms whose coverage consequently drops. These closures are thus viable as a natural experiment with which to establish causal effects of analyst coverage on a stock's information environment Kelly and Ljungqvist (2012) show that coverage termination has a significant price effect on other firms with correlated fundamentals, consistent with Admati (1985) and Veldkamp (2006a). The 43 closures from 2000 to 2008 provide a sample of exogenous coverage decline events[11] These coverage

[11] We thank Alexander Ljungqvist for sharing the data used in Kelly and Ljungqvist (2012). Please refer to their paper for details on the institutional background of these closure events. Hong and Kacperczyk (2010) use a similar identification strategy based on mergers of brokerage firms for an exogenous change in analyst coverage.

Table 5
Effect of contemporaneous earnings forecast revisions of bellwether firms on industry stock returns

Panel A: Regression of monthly stock returns on the contemporaneous earnings forecast revision of the bellwether firm

	Analyst coverage groups				
Independent variables	*All firms*	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
$FR_{IBW,t}$	0.185	0.285	0.266	0.148	0.040
	6.31	*9.91*	*4.80*	*5.84*	*1.01*
$FR_{k,t}$	0.900		0.734	0.966	1.219
	9.04		*13.05*	*6.99*	*5.68*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.130	0.074	0.125	0.172	0.214

Panel B: Regression of monthly stock returns on the contemporaneous and lagged earnings forecast revisions of the bellwether firm

$FR_{IBW,t}$	0.184	0.257	0.258	0.160	0.067
	5.89	*8.92*	*4.63*	*5.73*	*1.65*
$FR_{IBW,t-1}$	0.010	0.114	0.047	−0.032	−0.077
	0.31	*2.67*	*1.11*	*−0.81*	*−1.70*
$FR_{k,t}$	0.906		0.729	0.970	1.297
	8.91		*13.08*	*6.80*	*5.44*
$FR_{k,t-1}$	−0.037		0.092	−0.012	−0.312
	−1.54		*2.70*	*−0.32*	*−3.21*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.130	0.074	0.124	0.172	0.215
	Sum of the coefficients				
$FR_{IBW,t}$+$FR_{IBW,t-1}$	0.194	0.371	0.305	0.129	−0.011
	5.34	*7.69*	*4.40*	*3.73*	*−0.21*

In Table 5, Panel A we present the estimates of the following panel regression:

$$R_{k,t} = a_0 + b_1 FR_{IBW,t} + b_2 FR_{k,t} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7}$$

$$+ d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms k, excluding the industry bellwether firms. $R_{k,t}$ is firm k's stock return in month t. FR_{IBW} is the revision in consensus earnings forecasts for industry bellwether firm (i.e. same industry as firm k). FR_k, the revision in consensus earnings forecasts for firm k. Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. In Panel B, we add the lagged values of FR_{IBW} and FR_k to the regression model. The robust t-statistics clustered by industry are provided in *italics*.

declines allow us to examine whether affected firms exhibit abruptly larger spillovers from bellwether firms as less information is produced about them.

Denoting the closure month as event month 0, we test for changes in information spillovers by comparing a 3-month preevent period (month −3 to month −1) to a 3month postevent period (month +2 to month +4), omitting months 0 and 1 to exclude the actual event time[12] Specifically, we regress the monthly returns on each stock affected by a closure event on the lagged earnings forecast revisions of its bellwether firm through the preevent and

[12] We skip month 1 to ensure that the forecast revision computation does not depend on information from the event month.

postevent periods:

$$R_{k,t} = a_0 + b_{11}FR_{IBW,t-1} + b_{12}FR_{IBW,t-1}xDM\_POST_{k,t} + b_{13}FR_{IBW,t-1}xDM\_POST_{k,t}xLOWANAL_{k,t} + b_2FR_{k,t-1} + c_1R_{m,t} + c_2R_{m,t-1} + d_1R_{k,t1} + d_2R_{k,t-2,t-7} + d_3ln(SIZE_{k,t-1}) + d_4ln(BM_{k,t-1}) + d_5TURNOVER_{k,t-1} + d_6DM\_POST_{k,t} + e_{k,t} \quad (8)$$

where $DM\_POST_{k,t}$ is a dummy set to one in the postevent period and zero otherwise, and $LOWANAL_{k,t}$ is a dummy variable set to one if firm k is in the lowest tertile of analyst coverage in the preevent period. All other variables are as in Equation (6). The coefficients of interest in Equation (8) are the spillover from bellwether firms' forecast revisions, b_{11} the change in the spillover effect after the exogenous reduction of coverage for other stocks in general, b_{12}, and the extra effect for lowcoverage stocks (b_{13}). We expect the spillover effect to increase following a drop in coverage, especially for firms with low coverage.

As presented in Table 6, there is a significant increase in information spillover from bellwether firms to low-coverage firms that had an exogenous drop in coverage (i.e. b_{13} is positive and significant). The typical firm has an average decrease of one analyst following the closure of a brokerage firms in our sample. Consequently, we do not observe increases in the spillover effect for firms with high coverage because the drop is not likely to be economically important. The coefficients for all the control variables in Equation (8) are generally similar to those in Table 4, and some of the coefficients are weaker, possibly because of differences in sample size. We also observe higher stock returns during the postevent months (d_6), consistent with the decrease in liquidity resulting from the drop of coverage (Kelly and Ljungqvist 2012). Table 6 also shows that the estimates are unaffected if we exclude the stock's own forecast revisions, FR_k. In unreported results, our findings are unchanged if we drop the control variables in the regression.

To summarize, the results from the experiment arising from an exogenous drop in analyst coverage are consistent with our hypothesis that investors in thinly covered firms rely on information about bellwether firms to price the stocks, thus providing support for the information-spillover explanation for the bellwether effect.

4. Alternative Explanations and Robustness Checks

To conclude that the results above highlight a bellwether effect, we must show that they are not readily explained by other known results.

4.1 Is the bellwether effect driven by common analyst coverage?

Israelsen (2014) and Muslu, Rebello, and Ye (2014) find comovement in the returns of firms covered by the same analysts and attribute this to the analyst

Table 6
Analyst coverage terminations and the relation between stock returns and earnings forecast revisions of industry bellwether firms

Independent variables	Model 1 (number of events: 2462)	Model 2 (number of events: 2446)
Intercept	−2.524	−2.972
	−1.69	*−2.05*
$FR_{IBW,t-1}$	0.023	0.016
	0.24	*0.17*
$FR_{IBW,t-1}$*$DM\_POST_{k,t}$	−0.033	−0.043
	−0.17	*−0.22*
$FR_{IBW,t-1}$*$DM\_POST_{k,t}$*$LOWANAL_{k,t}$	1.058	1.406
	3.05	*3.92*
$DM\_POST_{k,t}$	1.280	1.295
	2.37	*2.45*
$FR_{k,t-1}$		−0.049
		−0.18
Other Controls	Yes	Yes
Rsq	0.178	0.178

In Table 6, we present the results of the following regression over the event window of 3 months before and 3 months after the brokerage closure event,

$$R_{k,t}=a_0+b_{11}FR_{IBW,t-1}+b_{12}FR_{IBW,t-1}*DM\_POST_{k,t}+b_{13}FR_{IBW,t-1}*DM\_POST_{k,t}*LOWANAL_{k,t}$$
$$+b_2FR_{k,t-1}+c_1R_{m,t}+c_2R_{m,t-1}+d_1R_{k,t-1}+d_2R_{k,t-2,t-7}+d_3ln(SIZE_{k,t-1})+d_4ln(BM_{k,t-1})$$
$$+d_5TURNOVER_{k,t-1}+d_6Ln(IO_{k,t-1})+d_7DM\_POST_{k,t}+e_{k,t}$$

for all firms k that experienced coverage terminations (Kelly and Ljungqvist 2012), excluding the industry bellwether firms. The exogenous coverage termination events are for the period 2000 to 2008. The month t stock returns, $R_{k,t}$, during the window is regressed on FR_{IBW} (the earnings forecast revision of firm k's industry bellwether firm) and its interactions with two dummy variables: DM_POST_k (equal to one in the postevent window) and $LOWANAL_k$ (equal to one if firm k has low analyst coverage in the preevent window). Model 1 (2) excludes (includes) firm k's revision in earnings forecasts, FR_k.Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$ the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust t-statistics clustered by industry are provided in *italics*.

using common information in forecasting all their earnings. Their findings do not affect our interpretation of the spillover to uncovered firms but might matter for low-coverage firms.

To check this, we reestimate Table 4, excluding firm-year observations in which the same analyst covers both the bellwether firm and the firms whose return is studied. Panel A of Table 7 summarizes these results, revealing significant point estimates on $FR_{IBW,t-1}$, very similar to those in Table 4. This shows that the bellwether effect is not driven by common analyst coverage. A second check repeats the exercise, removing all firm-year observations in which the analysts from the same brokerage firm cover both the bellwether firm and the firms whose return is studied. This step removes observations possibly tainted by analysts at the same institution sharing common information. Panel B of Table 7 shows that the Table 4 results remain intact. These results are perhaps unsurprising because our key findings are about relatively neglected firms, with zero or few analyst following, exhibiting the biggest spillover effects.

Table 7
Effect of lagged earnings forecast revisions of bellwether firms on industry stock returns, excluding firms sharing common analysts or brokerage firm with the bellwether firms

Panel A: Regression excluding firms sharing common analyst coverage

	Analyst coverage groups			
Independent variables	*All firms*	*Low coverage*	*Medium coverage*	*High coverage*
$FR_{IBW,t-1}$	0.084	0.138	0.048	0.055
	2.19	*2.73*	*1.14*	*0.86*
$FR_{k,t-1}$	0.120	0.122	0.158	−0.001
	6.09	*3.30*	*6.64*	*−0.02*
Other controls	Yes	Yes	Yes	Yes
Rsq	0.144	0.115	0.156	0.194

Panel B: Regression excluding firms sharing common brokerage firm

$FR_{IBW,t-1}$	0.098	0.165	−0.025	0.079
	1.40	*2.24*	*−0.27*	*0.73*
$FR_{k,t-1}$	0.163	0.128	0.252	0.084
	5.97	*2.86*	*4.84*	*0.71*
Other Controls	Yes	Yes	Yes	Yes
Rsq	0.110	0.102	0.122	0.126

In Table 7, we present the results of the following panel regression:

$$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1})$$
$$+ d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms k, excluding the industry bellwether firms. $R_{k,t}$ is firm k's stock return in month t. FR_{IBW} is the revision in consensus earnings forecasts for the industry bellwether firm. FR_k is the revision in earnings forecasts for firm k. The control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$ the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust t-statistics clustered by industry are provided in *italics*. In Panel A, the sample excludes all firms k that share common analyst coverage with its industry bellwether firm, and in Panel B, the sample excludes all firms k that share a common brokerage firm with its industry bellwether firm.

4.2 Do bellwethers just have more precise earnings forecasts?

Bellwether firms are followed by many analysts, so their consensus earnings forecasts might be more precise because of the law of large numbers. If so, bellwether firms' earnings might more usefully predict those of other firms purely because they are more precise. Therefore, we measure bellwether firms' forecast revisions by individual analysts, rather than by consensus forecasts, in two alternative ways.

First, we replace the bellwether firms' consensus earnings forecast revisions with the revision by a single analyst j, denoting this FR_{IBWj}. Specifically, we select the analyst whose forecast revision comes last in each month (measured, as in I/B/E/S, as month midpoint to month midpoint) and calculate her earnings forecast revision as this minus her prior forecast for this firm a month ago, scaled by the stock price at the prior month midpoint. If the prior forecast is over 3 months old, we regard it as stale, drop the analyst, and use the one with the second last forecast revision in the month in question. We reestimate Equation (6) using forecast revision by individual analysts.

Table 8
Effect of an individual analyst's revision of earnings forecast of bellwether firms on industry stock returns

	Analyst coverage groups				
Independent variables	*All firms*	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
$FR_{IBWj,t-1}$	0.009	0.071	0.036	−0.014	−0.040
	0.31	*1.84*	*0.82*	*−0.54*	*−1.58*
$FR_{k,t-1}$	0.096		0.123	0.113	0.029
	4.43		*3.46*	*3.93*	*0.62*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.127	0.074	0.120	0.166	0.206

In Table 8, we present the results of the following regression,

$$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1})$$
$$+ d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms k, excluding the industry bellwether firms. $R_{k,t}$ is the stock return in month t. FR_{IBWj} is the latest monthly revision in earnings forecasts for the industry bellwether firm made by analyst j in month $t-1$, and FR_k is the revision in the consensus earnings forecasts for firm k.Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$ the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust t-statistics clustered by industry are provided in *italics*.

In Table 8, we present the results. First, earnings forecast revisions of bellwether firms calculated as FR_{IBWj}, still significantly affect the prices of uncovered firms. Unsurprisingly, the point estimates are less than half as large as those in Table 4, based on consensus forecasts. Similar results ensue when we examine the effect of FR_{IBWj} on other firms' contemporaneous returns (not shown), where $FR_{IBWj,t}$ attracts a coefficient of 0.12 (t-statistics = 4.75) for zero-coverage firms and 0.093 (t-statistics = 2.32) for lowcoverage firms As a further test, we conduct a resampling exercise: randomly selecting an analyst's forecast revision each month, estimating Equation (6), and repeating this 10,000 times, which, in the regressions for zeroanalyst firms, generates an average coefficient on $FR_{IBWj,t-1}$ of 0.049 and 97% of individual estimates being significant at 5% level.

An alternative approach is to run an event study measuring the abnormal price reactions of other firms in the industry when an individual analyst revises her earnings forecast for the bellwether firm. This approach also addresses reverse causality more unequivocally because Ockham's razor weighs against analysts timing their revisions of bellwether firms' earnings forecasts to coincide precisely with neglected firms' prices moving *en masse* relative to risk benchmarks.

We first identify the precise date (event day 0) on which each individual analyst announces a revision to her earnings forecast for the bellwether firm. For each such event, we compute the cumulative abnormal return, $CAR_{k,w}$, for every firm $k$in the industry, excluding the bellwether firm, over an event window $w$days long. Following Gleason and Lee (2003), $CAR_{k,w}$ is stock k's cumulative w-day return in excess of the cumulative benchmark return over the same window. The tables report *CAR*s in excess of the market returns, but qualitatively similar results ensue using alternative benchmarks.[13]

To exclude confounding events, we apply two filters to the data. We exclude firms whose quarterly earnings announcement or own earnings forecast revision coincides with the event, defining coinciding as falling within a 5-day window around the event date: day -2 to day +2. We exclude forecast-revision events if the bellwether firm's earnings announcement coincides with the forecast revision, using the same 5-day window.

To analyze other firms' price responses to individual analysts updating their bellwether-firm forecasts, we run the following regression.

$$CAR_{k,w} = a_0 + b_1 FR\_Rank_{IBW} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + e_{k,w}, \tag{9}$$

where FR_Rank_{IBW} is the decile rank of each *bellwether firm's earnings forecast revision*, defined as the change in 1-year-ahead earnings forecast scaled by the stock price 1 month ago. This is computed using all bellwether-firm earnings forecast revisions during the year in question, so FR_Rank_{IBW} is 1 if the revision falls among the most negative 10% of all bellwether-firm forecast revisions in the calendar year and 10 if it is among the most positive 10%. All independent variables are defined in Equation (6). Firm characteristics are for the previous month. The equation is estimated separately for all nonbellwether firms, grouped by analyst coverage: zero-, low-, medium-, and high-analyst firms. We report the results of regressions explaining *CAR*s measured over a 2-day [0, 1] window around the event date and over a 21-day [2, 22] window after the date.

In Table 9, we present the results. In both the event [0, 1] and postevent [2, 22] windows, other firms' abnormal returns correlate significantly with the bellwether firm's earnings forecast revision. Moreover, this correlation is monotonically stronger for groups of other firms that are successively less covered. Uncovered and thinly covered firms exhibit the most significant reactions; other firms that are more intensely covered react less. Comparing the 2- and 21-day *CAR*s reveals a postevent stock-price drift, particularly for stocks followed by few or zero analysts.

These results combine to weigh against the bellwether effect being driven purely by a precision of information from averaging the forecasts of many analysts. The results of the event study are consistent with earnings forecast revisions of bellwether firms causing the price changes in the neglected firms, and thus corroborate our findings based on monthly consensus forecast revisions for the bellwether firms.

[13] Our results are robust to using alternative benchmarks such as the equal-weighted return on the matched size-decile portfolio and expected returns computed from a one-factor (the return on market portfolio in excess of the risk free rate) or Fama-French-Carhart four-factor models.

Table 9
Effect of individual analyst's revision of earnings forecast of bellwether firms on industry stock returns: An eventstudy analysis

	Analyst coverage groups				
Independent variables	*All firms*	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
CARs measured over the 2-day window [0, 1]					
$FR\_Rank_{I,BW}$	1.548	2.246	1.785	0.871	0.733
	4.86	*4.48*	*3.22*	*2.40*	*1.33*
Controls	Yes	Yes	Yes	Yes	Yes
Rsq (%)	0.027	0.043	0.037	0.015	0.011
*CAR*s measured over the 21-day window [2, 22]					
$FR\_Rank_{I,BW}$	6.517	6.721	9.396	5.491	3.601
	3.94	*3.72*	*4.35*	*2.52*	*1.57*
Controls	Yes	Yes	Yes	Yes	Yes
Rsq (%)	0.228	0.443	0.185	0.079	0.026

In Table 9, we report the tests of the effects of the earnings forecast revision of the industry bellwether firms by an analyst on the contemporaneous and postrevision returns on peer firms in the same industry. Specifically, we run the following regression:

$$CAR_{k,w} = a_0 + b_1 FR\_Rank_{I,BW} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1})$$

$$+ d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,w}$$

for all firms k, excluding the industry bellwether firms. $CAR_{k,w}$, is the cumulative return on stock k in excess of the market return over the w-day window around the industry bellwether firm's forecast-revision date (day 0). FR_Rank_{IBW} is the decile rank value of the earnings forecast revision using all industry bellwether firms each year (1 for the lowest decile and 10 for the highest decile). The control variables (not reported in the table) include $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$ the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust t-statistics clustered by industry are provided in *Italic*.

4.3 Are bellwether firms just early announcers?

Early announcers' earnings surprises explain both contemporaneous and future stock returns of late announcers in an industry (Thomas and Zhang 2008; see also Foster 1981; Han and Wild 1990; and Ramnath 2002; among others). Might bellwether firms just announce their earnings first, and so be the first to signal new industry information to analysts and investors?

Therefore, we drop all industry-months in which the bellwether firm makes an earnings announcement. Our (unreported) findings are unaffected, and the coefficient measuring the spillover is almost identical to that in Table 4. Thus, the bellwether effect causing return predictability and comovement is not driven by the effect stemming from early earning announcers.

4.4 Are we just observing reactions to common information?

Piotroski and Roulstone (2004) argue that analysts' firm-level earnings forecast revisions contain common industry information, and thus cause comovement among high-coverage firms. To isolate the information in bellwether-firm earnings forecast revisions beyond industry-level earnings information, we see if industry average earnings forecast revisions predict the returns of low- or zero-coverage firms in the following month. Specifically, we aggregate (value-weight) the earnings forecast revisions of all firms in the top tertile of analyst following in each industry each year, excluding the bellwether firm, and we reestimate Equation (6) by further controlling this variable. In unreported results, we find that the industry aggregate earnings forecast revision does not predict the subsequent month's returns of zero- and low-coverage firms, while the predictability of these firms' returns by bellwether-firm earnings forecast revisions remains. These tests weigh against the bellwether effect deriving from common industry information in analyst forecast revisions.

Lo and MacKinlay (1990) document a different commoninformation effect: large firms' stocks impound common information promptly, whereas small firms' stocks do so with a lag. Further, Hou (2007) documents slow diffusion of information from large firms within industries Could bellwether firms just be very large firms, and the bellwether effect just the lead-lag effect observed by Lo and MacKinlay (1990) and Hou (2007)?

To see if bellwether firms are simply reacting immediately to common information, which then enters other firms prices with a lag, we control for the predictive influence of the market portfolio return, and hence for market-wide information. We then also control for $R_{IBIG,t-1}$, the *lagged value-weighted return on a portfolio of large firms*, defined as the top decile by market capitalization in the industry, and hence for industry-wide information. We then run the following regression,

$$\begin{aligned} R_{k,t} = {} & a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + c_3 R_{IBIG,t-1} \\ & + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) \\ & + d_5 TURNOVER_{k,t-1} + e_{k,t} \end{aligned} \tag{10}$$

where all other variables are as in Equation (6).

We summarize the key results in Table 10. The coefficient c_3 in Equation (10) is significant across all of the different coverage groups, consistent with Lo and MacKinlay (1990) and Hou (2007). More importantly, the coefficient on the lagged bellwetherfirm earnings forecast revision is still significant, particularly for firms with low and zero coverage.

We explore this issue further by examining the relative size of bellwether firms. Although Table 3 shows that bellwether firms are generally large firms, only 7% of them are the largest one in the industry, and only 40% of them are in the top size-deciles in their industries. To see whether the bellwether effect is a size effect, we replace the bellwether-firm forecast revision with the forecast revision of the largest firm, by market capitalization, in each industry each year and rerun our tests. The results (not reported) show no significant spillover from the largest firms. Revisions to the largest firm's earnings forecasts do not significantly predict the subsequent returns of other firms in the industry in analogs to Equation (6), which control for the firm characteristics. Moreover, including forecast revisions for both the bellwether firm and the largest firm (deleting observations where they are the same firm), again reveals a significant spillover from the bellwether firm and none from the largest firm. Including

Table 10
Effect of lagged earnings forecast revisions of bellwether firms on industry stock returns: Controlling for lead-lag effects

	Analyst coverage groups				
Independent variables	*All firms*	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
$FR_{IBW,t-1}$	0.071	0.159	0.116	0.038	−0.031
	2.11	*3.79*	*2.51*	*0.96*	*−0.74*
$FR_{k,t-1}$	0.104		0.131	0.118	0.044
	5.02		*3.98*	*4.34*	*1.00*
$R_{IBIG,t-1}$	0.114	0.117	0.128	0.119	0.075
	5.30	*4.87*	*4.54*	*5.56*	*4.38*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.126	0.075	0.120	0.164	0.204

In Table 10, we present the results of the following panel regression:

$$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + c_3 R_{IBIG,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7}$$

$$+ d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms k, excluding the industry bellwether firms. $R_{k,t}$ is firm k's stock return in month t. FR_{IBW} is the revision in consensus earnings forecasts for the industry bellwether firm. FR_k is the revision in consensus earnings forecasts for firm k. R_{IBIG} is the value-weighted return of stocks in the same industry that belong to the top decile in terms of market capitalization. Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month $t-7$ to month $t-2$; $SIZE_k$ the market capitalization; BM_k, the booktomarket equity ratio; $TURNROVER_k$ the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust t-statistics clustered by industry are provided in *italics*.

firm-size decile dummies in Equation (6) to allow nonlinear size effects also leaves our results unchanged.

These results weigh against the bellwether effect being driven by common industry information, or being a firmsize effect or lead-lag effect associated with firm size.

4.5 Is the bellwether effect confined to illiquid stocks?

Firms with zero or low analyst coverage might be extremely illiquid stocks; and one explanation of the Lo and MacKinlay (1990) lead-lag finding is that illiquid stocks react with a lag to common information because their prices do not adjust until nontrivial trading occurs. If zero- and low-coverage firms are illiquid, and bellwether firms are liquid, the bellwether effect we observe might be a liquidity effect in disguise.

We follow Amihud (2002) in defining a monthly *illiquidity* measure as $[1/n \sum \{|R_{j,d}|/ (P_{j,d} * N_{j,d})\}]$, where n is the number of trading days in the month, $|R_{j,d}|$is stock$j$'s absolute return on day d, $P_{j,d}$ is its daily closing price, and $N_{j,d}$ is the number of its shares traded on day d. For a given trading volume, the greater the price change, the higher the Amihud *illiquidity* measure.

We then reestimate Equation (6), dropping the most illiquid decile of firms in each industry each year, measured at the previous year-end. The coefficients on FR_{IBW} (not reported) are similar in magnitude to those in Table 4, and significant for zeroanalyst firms (coefficient = 0.13; t = 2.75) and lowanalyst firms (coefficient = 0.12; t = 2.47). Repeating this by dropping the 30% least liquid stocks in each industry each year also generates similar and significant point estimates for zero- or lowcoverage firms

These findings weigh against the bellwether effect being driven by highly illiquid stocks. Additionally, the results in Section 3.1 showing low (and zero) coverage firms exhibiting larger contemporaneous price reactions to bellwetherfirm earnings forecast revisions are also inconsistent with explanations of lagged adjustment because of illiquidity or lead-lag effects.

4.6 Is the bellwether firm unique?

Another issue is the uniqueness of bellwether firms. In Table A1, we summarize the distributions of *PCORR_ROA* by year and industry. As the dispersion in *PCORR_ROA* varies across industries, it is possible that there are multiple bellwether firms in some industries and perhaps weak bellwether effects in others. The bellwether firm's *PCORR_ROA*s are well above the rest of the distribution, except in agriculture, candy and soda, and real estate. When we remove these three industries from our sample, the bellwether effect becomes stronger, as expected.

To explore whether the bellwether firm is unique, we rerun our regressions substituting a "second-best" alternative bellwether firm: after dropping all bellwether firms, the firm with the highest *PCORR_ROA* among the top and middle tertiles of analyst coverage, rather than the highest *PCORR_ROA* among the top tertile of coverage (our bellwether firm criterion). In unreported results, the spillover from this alternative bellwether firm's lagged forecast revision is also significant for zero-coverage firms, but it is weak in predicting other firms' returns (including the low-coverage firms). The weaker predictive effect of the alternative bellwether firm is attributable to its lower *PCORR_ROA* or lower analyst coverage relative to our bellwether criterion. This is also illustrated by the weak spillover effects when we select the alternative bellwether firm to be the one with second highest *PCORR_ROA* among the top tertile of analyst coverage. Thus, an industry might have more than one viable bellwether firm, with alternatives more viable if their *PCORR_ROA* and analyst coverage nears that of the firm our procedure selects.

4.7 Further evidence: Is institutional trading consistent with a bellwether effect?

Financial practitioners commonly refer to bellwether stocks.[14] If the phenomenon is real, it might be evident in institutional investor trades. Therefore, we examine institutional trading around revisions in the forecasted earnings of bellwether firms to see if institutional traders react by trading in other firms whose fundamentals are correlated with those of the bellwether firm.

[14] Investopedia.com defines a *bellwether stock* as "a stock that is believed to be a leading indicator of the direction of a sector, industry, or market as a whole." Other popular investment sites and news articles use similar definitions.

We employ the intraday transactions data on institutional trades provided by Ancerno over the period January 2001 to December 2009. This database contains a complete history of transactions by Ancerno's institutional clients. This database has been extensively used in several studies, including Irvine, Lipson, and Puckett (2007); Anand et al. (2012); and Hu et al. (2014).

We focus on individual analysts' revisions to their earnings forecasts for our bellwether firms as events because these are precisely datable, and examine institutional investors' trades around these event dates. To remove observations contaminated by confounding events, we drop observations where the bellwether firm announces quarterly earnings in a 5-day window (day -2 to +2) around the event date. For each bellwether forecast-revision event, we construct $ABNetBuy_{k,w}$, abnormal daily net institutional buying of the stock of each firm k in the industry, averaged over a w-day window around the event.

We construct this variable as follows: First, we follow Irvine, Lipson, and Puckett (2007) in defining net institutional buying of firm k's shares on day d, $NetBuy_{k,d}$, as the number of shares purchased minus the number of shares sold by all institutional investors in the database, scaled by firm k's shares outstanding. $NetBuy_{k,d}$ is set to zero if Ancerno records no institutional trading of stock k on day d. Second, we compute $NetBuy_{k,pre}$, the average of $NetBuy_{k,d}$ in a 3-month preevent window (day -73 to day -11) ending 10 days before the event date, to use as a benchmark against which to assess abnormal net institutional buying. Finally, we follow Malmendier and Shantikumar (2007) and Barber and Odean (2008) in standardizing abnormal net institutional buying by the standard deviation of daily institutional net buying over the preevent window, $STD(NetBuy_{k,pre})$. Thus, the average abnormal daily institutional net buying in firm k's stock is

$$ABNetBuy_{k,w} = \frac{1}{W}\sum_{d=1}^{W}\left(\frac{NetBuy_{k,d} - NetBuy_{k,pre}}{STD(NetBuy_{k,pre})}\right). \tag{11}$$

We estimate $ABNetBuy_{k,w}$ in two event windows: [0,1], a 2-day window from day 0 to day 1 around the forecast-revision date 0; and [2,22], a 21-day window from day 2 to day 22 after the event date.

Our tests separate upward and downward revisions in bellwether firms' earnings forecast. This is because arbitrage requiring buying shares is less costly than arbitrage requiring shorting (Shleifer and Vishny 1997; Bris, Goetzmann, and Zhu 2007) and short-sale restrictions constrain institutional investors reporting to Ancerno (Arif, Ben-Repheal and Lee 2014). Consequently, an asymmetric response is possible. Upward revision to a bellwether firm's forecasted earnings might induce institutional investors to buy more shares in other firms than similar downward revision would induce them to sell.

In Panel A of Table 11, we report average abnormal daily institutional trading of shares in other firms in the industry around revisions to the relevant bellwether firms' forecasted earnings. Following positive bellwether forecast revisions, abnormal institutional net buying of peer firms is significant for

Table 11
Earnings forecast revisions of bellwether firms and institutional trading in industry stocks

Panel A: Abnormal net purchase in peer firms in response to positive/negative earnings forecast revisions of industry bellwether firms

	Analyst coverage groups				
	All firms	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
2-day [0, 1] window					
Negative FR_{IBWj}	0.005	0.052	0.009	0.000	0.002
	0.76	*1.41*	*0.56*	*0.05*	*0.22*
Positive FR_{IBWj}	0.016	0.095	0.060	0.012	−0.011
	2.11	*2.47*	*2.81*	*1.29*	*−1.33*
21-day [2, 22] window					
Negative FR_{IBWj}	0.005	0.023	0.009	0.004	−0.002
	0.78	*1.17*	*0.93*	*0.50*	*−0.26*
Positive FR_{IBWj}	0.017	0.055	0.042	0.009	−0.014
	2.52	*2.86*	*3.57*	*1.06*	*−1.92*

Panel B: Abnormal net purchase in peer firms in response to small/large earnings forecast revisions of industry bellwether firms

	All firms	*No coverage*	*Low coverage*	*Medium coverage*	*High coverage*
2-day [0, 1] window					
Large negative FR_{IBWj}	−0.018	0.004	−0.104	−0.002	−0.003
	−1.28	*0.06*	*−2.18*	*−0.07*	*−0.13*
Small negative FR_{IBWj}	0.007	0.066	0.027	−0.004	0.003
	0.91	*1.60*	*1.56*	*−0.41*	*0.34*
Small positive FR_{IBWj}	0.018	0.083	0.066	0.014	−0.009
	2.07	*1.95*	*2.48*	*1.14*	*−0.93*
Large positive FR_{IBWj}	0.009	0.166	0.049	0.016	−0.021
	0.51	*2.38*	*1.26*	*0.72*	*−0.83*
21-day [2, 22] window					
Large negative FR_{IBWj}	−0.008	−0.026	−0.022	−0.009	0.005
	−0.75	*−0.75*	*−1.01*	*−0.53*	*0.37*
Small negative FR_{IBWj}	0.006	0.035	0.015	0.003	−0.007
	0.85	*1.72*	*1.58*	*0.41*	*−0.92*
Small positive FR_{IBWj}	0.017	0.050	0.042	0.010	−0.013
	2.44	*2.42*	*3.30*	*1.15*	*−1.70*
Large positive FR_{IBWj}	0.020	0.080	0.055	0.003	−0.011
	1.99	*2.50*	*2.44*	*0.20*	*−0.97*

In Table 11, Panel A we present the average daily abnormal net purchase by institutional investors in firms in the same industry (excluding the bellwether firm) in response to the negative and positive revisions of earnings forecasts of bellwether firms by individual analysts (FR_{IBWj}), calculated as the change in earnings forecasts scaled by the stock price at least 30 days before the revision date. For each forecast-revision event, the abnormal net purchase for an industry-peer stock k over a specific w-day event window around the revision date (day 0) is calculated as the difference between the average daily net purchase in the event window and the 63-day [−73, −11] preevent window, scaled by the standard deviation of daily net purchase in the preevent window, where daily net purchase is calculated as the difference between the number of shares purchased and the number of shares sold by all institutional investors on the day, scaled by the number of shares outstanding. The abnormal net purchase at the event level is the average of firm-level abnormal net purchases, reported separately for different groups of stocks sorted on analyst coverage. Finally, event-level abnormal net purchase is averaged across events in the same calendar month to obtain $ABNetBuy_w$, and we report the mean and the associated *HAC* t-statistic. $ABNetBuy_w$ is reported for a 2-day [0, 1] and 21-day [2, 22] windows around the forecast-revision date. In Panel B, we present the average daily abnormal net purchase by institutional investors in firms in the same industry (excluding the bellwether firm) in response to the large and small revisions of earnings forecasts of bellwether firms by individual analysts (FR_{IBWj}), where *large (small)* FR_{IBWj} is defined as FR_{IBWj} above (below) 1%, in absolute value.

zero- and low-coverage firms, but not for firms with better coverage. Abnormal institutional buying of thinly covered firms is significant in both the 2-day and 21-day windows. It is not surprising that the average abnormal daily buying by institutions is higher in the 2-day window. Interestingly, the abnormal buying of thinly covered firms continues to spread over the following month, consistent with our spillover findings in stock returns.

We find institutional investors buying up shares in other firms in a bellwether firm's industry when analysts revise the latter's earnings forecasts upward: $ABNetBuy_k$ following the revision is largest and most significant among other firms with scanter coverage. These results are consistent with information spillover from the bellwether firm to other firms in the industry.

In contrast, downward revisions to bellwether firm's forecasted earnings do not appear to stimulate abnormal institutional investor selling of other firms' shares. To investigate this asymmetry further, we define large forecast revisions to bellwether-firm earnings forecasts as being greater than 1% in absolute value. Small earnings forecast revisions are those less than 1% in absolute value. Panel B of Table 11 reveals abnormal net institutional selling ($ABNetBuy_k$ <0) of other firms' shares following large negative revisions to the relevant bellwether firm's forecasted earnings. However, abnormal institutional selling is statistically significant for low-coverage firms in the 2-day event window only. This weaker information spillover for downward earnings revisions is consistent with short sales being costly or restricted for these institutions.

Further, Panel B shows significant abnormal institutional buying of low- (or zero-) coverage firms following both small and large positive revisions to bellwether firms' forecasted earnings. Abnormal institutional buying of low-coverage stocks is significant in both the 2-day and 21-day event windows. However, institutions do not appear to engage in abnormal buying of other firms that are themselves heavily covered by analysts.

Overall, patterns in institutional trading around revisions in analysts' earnings forecasts for bellwether firms corroborate the propositions in Section 1. These patterns support interpreting the results in Table 4 as demonstrating a bellwether effect.

5. Conclusions

Information spillover from "bellwether firms," defined as firms with very heavy analyst coverage and fundamentals highly correlated with those of other firms in the same industry, affects the values of those other firms shares, both contemporaneously and with a lag. The spillover is especially evident for other firms followed by few or no analysts. The spillover is unidirectional: revisions to the bellwether firm's forecasted earnings affect the returns of other firms in the industry that have less or no coverage; revisions to the forecasted earnings of other firms with less or no coverage do not affect the bellwether firm's returns, either contemporaneously or with a lag. The information spillover is not obviously driven by other known phenomena. The findings survive controls for delays in price adjustment to common information (Lo and MacKinlay 1990; Hou 2007), common coverage (Israelsen 2014; Muslu, Rebello, and Ye 2014), and forecast precision. The effect is more pronounced in sparsely covered firms after they experience exogenous drops in coverage caused by brokerage firms closing their research departments.

These findings imply that investors use information produced by analysts who follow bellwether stocks to price other stocks. This necessarily causes heavily covered stocks to comove more with other stocks and, therefore, with industry and market indexes. Thus, stocks that are more broadly followed exhibit more comovement precisely because they are more information-laden, letting investors use them to value many other less heavily followed stocks.

Further, the findings accord well with the predictions of models of profit-maximizing information intermediaries producing information with large fixed-cost technologies, which thereby skew their output to produce more information useful in valuing many stocks and less information useful in valuing only one (Veldkamp 2006a). If so, lower fixed costs of information production would induce analysts to extend coverage to more firms; thus reducing information spillovers and leaving individual firms' stock returns more idiosyncratic.

Appendix

Table A1
Summary statistics of *PCORR_ROA*

Panel A: Summary statistics by year

Year	BW	Mean	Std.	Q1	Median	Q3
1984	0.190	0.112	0.046	0.076	0.107	0.147
1985	0.205	0.131	0.048	0.093	0.125	0.166
1986	0.194	0.123	0.043	0.089	0.119	0.152
1987	0.184	0.112	0.040	0.082	0.108	0.140
1988	0.170	0.110	0.040	0.078	0.107	0.140
1989	0.193	0.116	0.047	0.080	0.110	0.150
1990	0.201	0.126	0.047	0.089	0.120	0.159
1991	0.191	0.126	0.040	0.095	0.123	0.153
1992	0.183	0.113	0.038	0.085	0.110	0.140
1993	0.186	0.110	0.041	0.077	0.105	0.139
1994	0.201	0.117	0.048	0.081	0.110	0.151
1995	0.196	0.113	0.043	0.078	0.110	0.143
1996	0.201	0.114	0.045	0.078	0.107	0.144
1997	0.205	0.118	0.047	0.080	0.111	0.150
1998	0.205	0.118	0.046	0.082	0.113	0.148
1999	0.183	0.110	0.042	0.076	0.105	0.141
2000	0.186	0.111	0.042	0.079	0.107	0.139
2001	0.187	0.113	0.042	0.080	0.107	0.142
2002	0.161	0.102	0.035	0.076	0.098	0.127
2003	0.176	0.102	0.038	0.072	0.096	0.126
2004	0.198	0.112	0.045	0.077	0.106	0.143
2005	0.185	0.108	0.043	0.073	0.101	0.139
2006	0.177	0.102	0.041	0.069	0.096	0.133
2007	0.176	0.105	0.042	0.070	0.100	0.136

(*continued*)

Table A1
Continued

Year	BW	Mean	Std.	Q1	Median	Q3
2008	0.219	0.126	0.054	0.082	0.122	0.167
2009	0.196	0.116	0.050	0.074	0.109	0.153
2010	0.194	0.115	0.047	0.078	0.112	0.149
2011	0.196	0.114	0.045	0.078	0.110	0.146

Panel B: Summary statistics by industry

Industry	BW	Mean	Std.	Q1	Median	Q3
Agriculture	0.175	0.131	0.060	0.079	0.123	0.173
Food products	0.144	0.096	0.030	0.074	0.093	0.116
Candy & soda	0.124	0.100	0.038	0.067	0.106	0.124
Beer & liquor	0.219	0.125	0.065	0.071	0.122	0.175
Recreation	0.170	0.112	0.040	0.083	0.107	0.138
Entertainment	0.139	0.098	0.033	0.072	0.094	0.119
Printing & publishing	0.192	0.114	0.046	0.079	0.109	0.147
Consumer goods	0.162	0.101	0.034	0.075	0.099	0.123
Apparel	0.185	0.115	0.037	0.085	0.113	0.141
Healthcare	0.197	0.115	0.044	0.081	0.110	0.144
Medical equipment	0.179	0.101	0.035	0.074	0.096	0.122
Pharmaceuticals	0.202	0.108	0.038	0.079	0.102	0.132
Chemicals	0.162	0.098	0.032	0.074	0.094	0.118
Rubber & plastics	0.132	0.095	0.029	0.074	0.093	0.114
Textiles	0.164	0.109	0.038	0.079	0.107	0.136
Construction materials	0.185	0.111	0.041	0.080	0.106	0.138
Construction	0.199	0.121	0.050	0.079	0.118	0.158
Steel works	0.208	0.125	0.048	0.089	0.121	0.160
Fabricated products	0.141	0.102	0.038	0.073	0.099	0.125
Machinery	0.209	0.112	0.041	0.080	0.105	0.139
Electrical equipment	0.170	0.103	0.035	0.076	0.098	0.125
Automobiles & trucks	0.193	0.118	0.044	0.085	0.114	0.149
Aircraft	0.185	0.129	0.059	0.082	0.124	0.171
Shipbuilding & railroad equip.	0.204	0.155	0.077	0.094	0.157	0.215
Defense	0.131	0.096	0.048	0.046	0.097	0.138
Precious metals	0.137	0.106	0.042	0.072	0.104	0.131
Nonmetallic & industrial metal mining	0.191	0.133	0.060	0.082	0.126	0.184
Coal	0.148	0.105	0.048	0.065	0.101	0.136
Petroleum & natural gas	0.227	0.131	0.053	0.088	0.125	0.173
Utilities	0.351	0.210	0.109	0.109	0.206	0.321
Communication	0.173	0.101	0.035	0.076	0.096	0.123
Personal services	0.166	0.102	0.035	0.076	0.099	0.127
Business services	0.195	0.104	0.036	0.077	0.098	0.127
Computer hardware	0.176	0.102	0.035	0.076	0.097	0.124
Computer software	0.196	0.106	0.037	0.079	0.100	0.131
Electronic equipment	0.214	0.106	0.038	0.077	0.099	0.129
Measuring & control equip.	0.177	0.100	0.035	0.073	0.095	0.121
Business supplies	0.217	0.120	0.051	0.078	0.110	0.155
Shipping containers	0.164	0.119	0.051	0.081	0.116	0.155
Transportation	0.193	0.114	0.043	0.081	0.109	0.146
Wholesale	0.171	0.103	0.032	0.080	0.100	0.122
Retail	0.298	0.153	0.070	0.096	0.142	0.207
Restaurants & hotels	0.179	0.106	0.036	0.078	0.102	0.130
Banking	0.250	0.126	0.052	0.085	0.118	0.163
Insurance	0.216	0.118	0.048	0.082	0.110	0.154
Real estate	0.107	0.083	0.028	0.061	0.079	0.102
Trading	0.222	0.123	0.049	0.083	0.115	0.157

In Panel A, we present the summary statistics of *PCORR_ROA*, the partial correlation of a firm's earnings (returns on assets or *ROA*) for each year, with earnings of other firms in the same industry. For each industry each year, we obtain the bellwether firm's *PCORR_ROA* and the mean, median, standard deviation, and twenty-fifth (Q1) and seventy-fifth (Q3) percentile values of *PCORR_ROA* for all firms. Finally, we average the industry-year statistics across all industries in each year. In Panel B, we present the summary statistics of *PCORR_ROA* for each industry. First, we obtain the statistics for each industry, each year, and then average industry-year statistics across all years in an industry.

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