Geographic Lead-Lag Effects

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Backgrounds & Motivation

- Stock prices of firms with common characteristics such as industry and geographic position tend to move together. However, empirical studies document significant lead-lag relationships.
- Lead-lag profits tend to be modest when the “lagging” firm is heavily covered by analysts.
- Analysts tends to specialize by industrial sector rather than geography.

- How to understand the channel linking the scrutiny level to observed lead-lag relationships more explicitly, not only by individual analyst coverage but also by shared one?
- Can it be inspired with the help of geographic lead-lag effects?

Why headquarters locations?

1. Both geographic position and industry group firms by their sensitivity to common fundamental shocks, causing lead-lag effects.

2. It help distinguish between analyst coverage measured at the level of the individual firm, and between pairs of firms. Analysts specialize by industrial sector instead of geographic position. A higher individual analyst following is almost certain to generate significant overlaps with industry peers. The geography sorting criteria should not generate substantial overlaps in analyst coverage.

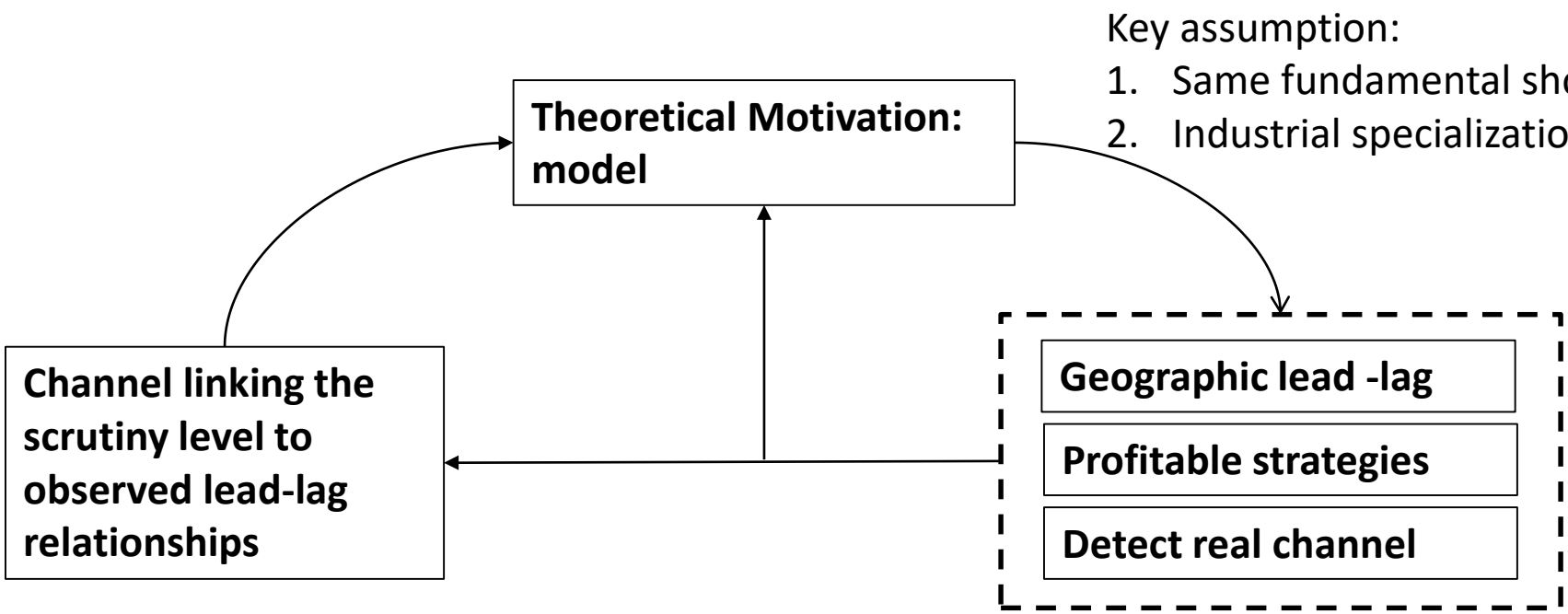
Research Problem

- What is the real channel linking the scrutiny level to observed lead-lag relationships?
  - ➢With the help of geographic lead-lag effects, we find analysts common to both leading and lagging firms are important may be a more useful concept for predicting relative mispricing.

Contribution

- The first to explicitly tie the nature of the lead-lag relation to the organization of the analyst community.
- More explicitly understand the channel linking the level of scrutiny to observed lead-lag relationships.

Outline


Key assumption:
1. Same fundamental shocks
2. Industrial specialization
Theoretical Motivation: model
Channel linking the scrutiny level to observed lead-lag relationships
Geographic lead -lag
Profitable strategies
Detect real channel

Model Design: Theoretical Motivation

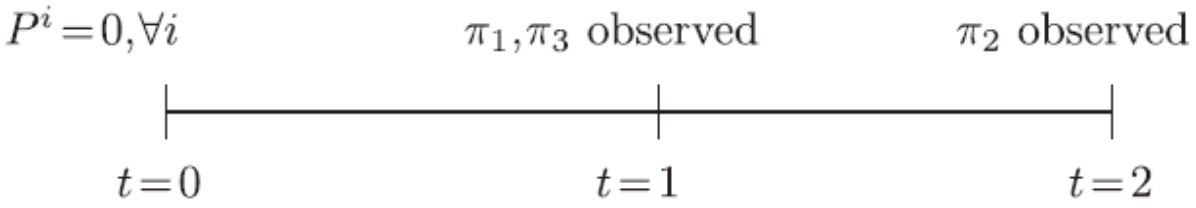
- industries A and B; locations X and Y; three firms i ∈{1,2,3}
- local shock L, industry shock I
- the realization of firm i's liquidating dividend at t=2:

$$\pi_1 = I_A + L_X + \epsilon_1$$

$$\pi_2 = I_A + L_Y + \epsilon_2$$

$$\pi_3 = I_B + L_Y + \epsilon_3.$$

- Time line:



Model Design: Theoretical Motivation

- four possible reports analyst can choose: {π1,π3},{π1},{π3},{}
- Investor set the price of firm 2 as: $P_{t=1}^{2} = E[\pi_2 | (r_1, r_2, r_3, \ldots r_N)]$
- the stock price of firm 2 at t =1 can take on four possible values:

$$P_{t=1}^{2} = \begin{cases} 0 & \text{if neither } \pi_1 \text{ nor } \pi_3 \text{ reported,} \\ \pi_1 \left(\frac{\sigma_I^2}{\sigma_I^2 + \sigma_L^2 + \sigma_\epsilon^2} \right) & \text{if only } \pi_1 \text{ reported,} \\ \pi_3 \left(\frac{\sigma_L^2}{\sigma_I^2 + \sigma_L^2 + \sigma_\epsilon^2} \right) & \text{if only } \pi_3 \text{ reported,} \\ \pi_1 \left(\frac{\sigma_I^2}{\sigma_I^2 + \sigma_L^2 + \sigma_\epsilon^2} \right) + \pi_3 \left(\frac{\sigma_L^2}{\sigma_I^2 + \sigma_L^2 + \sigma_\epsilon^2} \right) & \text{if both } \pi_1 \text{ and } \pi_3 \text{ reported.} \end{cases}$$

- the probability of π1 / π3 being reported p1(N) / p3(N)
- Industry momentum occurs when:

$$cov(P_{t=1}^{1} - P_{t=0}^{1}, P_{t=2}^{2} - P_{t=1}^{2}) = cov(\pi_1, \pi_2 - P_{t=1}^{2}) = \sigma_I^2 (1 - p_1(N))$$

- Regional momentum takes a similar form:

$$cov(\pi_3 - 0, \pi_2 - P_{t=1}^{2}) = \sigma_L^2 (1 - p_3(N))$$

Model Design: Data

- Sample:

1. domestic common stocks traded on the NYSE, NASDAQ, and AMEX over the period 1970 – 2013

2. stocks headquartered in or proximate to, the twenty largest urban centers in the United States

- Firm location variable: based on the ZIP code corresponding to its headquarters' location in the Compustat database.
- Industry classification: we monthly link each firm to a single Fama-French 12 industry, which groups firms by SIC designations

Empirical Results: Validate Key Assumptions

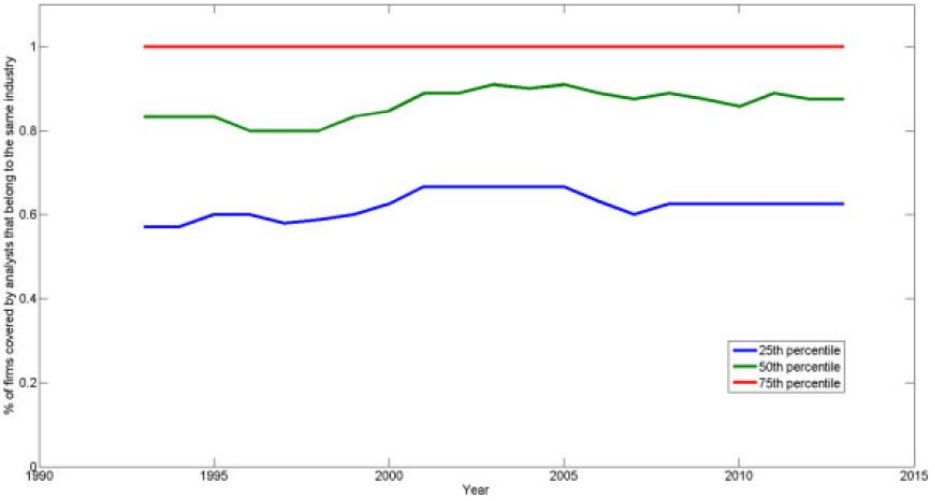
- Geographic effects on firms' performance: panel regressions of individual firms' fundamental X onto their contemporaneous city portfolio for the same variable X

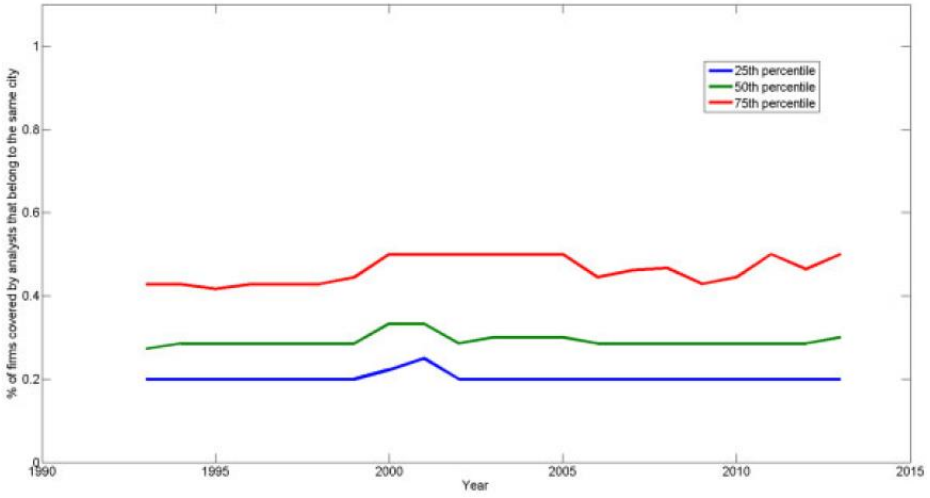
Area comovement in fundamentals

	ΔEPS	ΔSales	ΔEmployees	ΔNewCapital_EV	Returns monthly	Returns annual
city	.151***	.164***	.178***	.210***	.228***	.298***
	(4.70)	(5.98)	(5.92)	(6.61)	(16.59)	(6.91)
industry	.641***	.634***	.633***	.671***	.927***	.949***
	(20.68)	(26.48)	(24.16)	(27.33)	(88.04)	(18.70)
R^2	9.71%	26.13%	19.54%	26.66%	13.75%	21.36%
Observations	125,196	149,153	133,220	86,598	1,626,775	124,956
Time FE	Y	Y	Y	Y	Y	Y
# time clusters	54	66	66	47	528	44
Firm FE	Y	Y	Y	Y	Y	Y
# firm clusters	12,103	13,232	12,401	9,433	13,033	12,193

Empirical Results: Validate Key Assumptions

- Analyst specialization by industry





➢ About 83% of the stocks covered were in the same industry while 28% in the same city.

Empirical Results: Validate Key Assumptions

- Analyst specialization by industry:

	Full sample	*Firms with 1-3 analysts*	*Firms with 4-9 analysts*	*Firms with 10+ analysts*
Avg # of analysts	4.81	1.83	5.84	13.81
Overlaps between geographic peers				
% firm-years with zero overlap	57.93%	68.87%	49.37%	38.28%
# of peers connected via at least one overlap	2.08	0.84	2.61	5.55
Overlaps between industry peers				
% firm-years with zero overlap	7.39%	12.67%	2.32%	0.49%
# of peers connected via at least one overlap	15.73	5.81	19.05	45.95

➢ Firms within the same industry tend to be covered by a common set of analysts.

Empirical Results: Main Results

- Establish the presence of lead-lag effects:

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin c,j,t} + \beta_3 X_t + \epsilon_{i,c,j,t+1}$$

Predictability of stock returns by area and industry portfolios with controls (Fama-MacBeth)

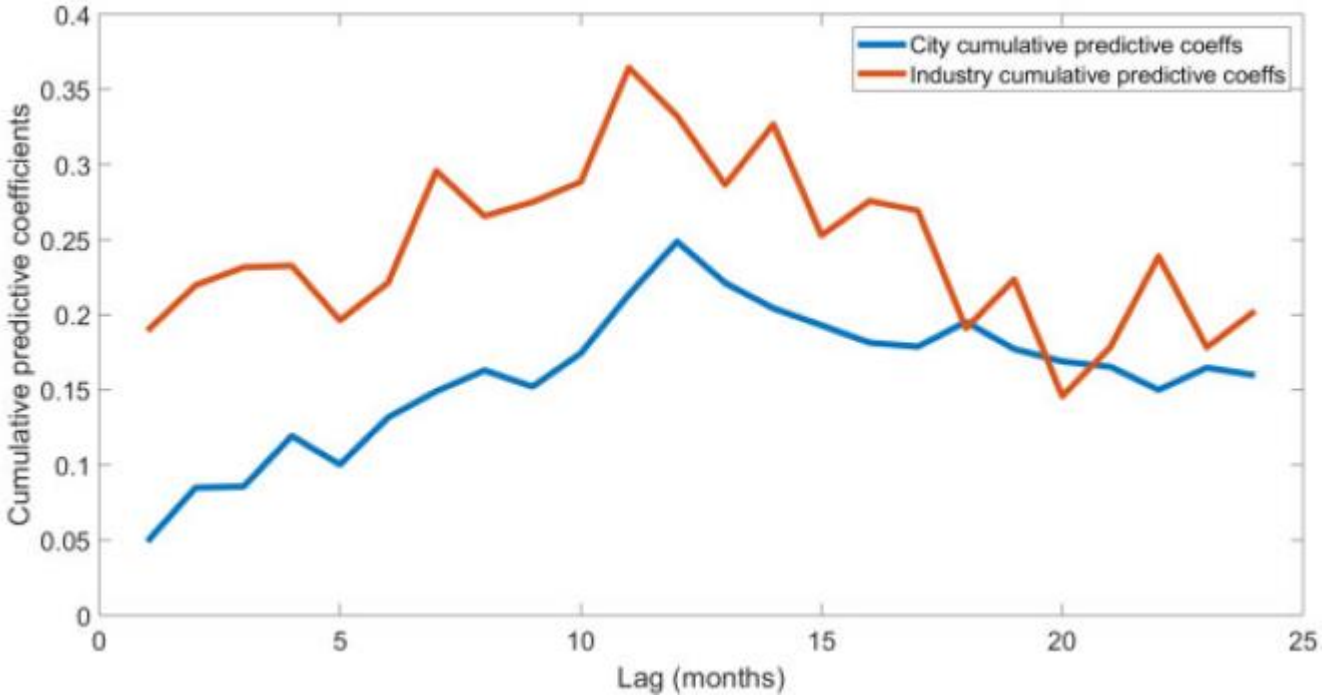
A. Individual stock returns

	full sample	*1970-1990*	*1991-2013*
$r_{city,t-1}$	.061***	.066***	.057***
	(5.11)	(3.81)	(3.45)
$r_{industry,t-1}$	.243***	.249***	.239***
	(11.71)	(8.26)	(8.34)
Avg R^2	6.48%	6.55%	6.42%
Observations	1,458,783	481,729	977,054
# time clusters	516	240	276

- Both β1 and β2 are significant, with lead-lags within cities being one-fourth as strong as those within industry groups.

Empirical Results: Main Results

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin c,j,t} + \beta_3 X_t + \epsilon_{i,c,j,t+1}$$



- The 1-month lagged return is an important predictor. Realizations of the geographic factors are incorporated into stock prices much more slowly. Overreaction to industry factors.

Empirical Results: Main Results

- How to create profitable trading strategies? - Every month, we rank each firm by the average lagged 1-month return of firms (same city, different industry) and form VW portfolios with 1-month holding period.

Momentum trading strategy, quintiles

	Mean (%)	*CAPM α*	*t-stat*	*FF-3 α*	*t-stat*
Lowest city return	0.735	−0.258	−3.228	−0.244	−3.011
	0.876	−0.077	−1.112	−0.038	−0.520
	1.027	0.109	1.432	0.127	1.583
	0.949	−0.009	−0.102	−0.002	−0.022
Highest city return	1.158	0.212	3.196	0.211	3.029
5-1 spread	0.423 [3.65]	0.471	[4.16]	0.455	[3.99]

➢ A geographic momentum strategy is profitable, but appears unrelated to standard risk factors.

Empirical Results: Main Results

- Which measure of analyst coverage is most relevant when thinking about lead-lag effects on stock returns?

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin c,j,t} + \beta_3 X_t + \epsilon_{i,c,j,t+1}$$

A. Number of analysts

	(0)	*(1-4)*	*(5-9)*	*(10+)*	Δ High/Low
$r_{city,t-1}$	0.067***	0.060**	0.090***	0.060***	
	(3.63)	(3.27)	(4.12)	(2.76)	[0.877]
$r_{industry,t-1}$	0.283***	0.245***	0.140***	0.098**	
	(8.79)	(8.83)	(4.64)	(3.54)	[0.00***]
Avg R^2	6.42%	7.33%	10.72%	13.98%	
Observations	503,536	317,030	167,289	170,333	
# time clusters	336	336	336	336	

- Analyst overlap plays an important role in the relative stock price efficiency between companies subject to common shocks.

Empirical Results: Main Results

	Regressions with overlaps		
	(1)	*(2)*	*(3)*
$r_{city,t-1}$	0.070***	0.056***	0.056***
	(5.86)	(4.41)	(4.38)
$r_{industry,t-1}$	0.245***	0.264***	0.265***
	(11.65)	(12.21)	(12.24)
$city_{i,t-1} * city_{overlap,i,t-1}$	−.000		−.004
	(−0.03)		(−0.32)
$industry_{i,t-1} * industry_{overlap,i,t-1}$	−.011***		−.008**
	(−3.01)		(−2.25)
$city_{i,t-1} * city_{numofanalysts,i,t-1}$		.006	.006
		(1.43)	(1.46)
$industry_{i,t-1} * industry_{numofanalysts,i,t-1}$		−.017*	−.017*
		(−1.83)	(−1.79)

- Analyst overlap plays an important role in the relative stock price efficiency between companies subject to common shocks.

Robustness and Extensions

- mis-measured headquarters' locations
- regional predictability for more all less regionally concentrated firms
- time fixed effects
- one month delayed portfolio formation
- control other sources of lead-lags such as firm size, analyst coverage, customers and suppliers relationships, institutional ownership…

Conclusion

- We find that regionally sorted portfolios generate trading profits that are a quarter to half as large as those using industry sorts.
- Because of the way that analysts are organized, lead-lags between non-industry local peers are comparatively invariant to sorts on analyst coverage.
- We develop a simple model and conduct empirical research, and conclude that shared analyst coverage may be more useful to predict relative mispricing.