A Simple Multimarket Measure of Information Asymmetry

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- **Education**

B.S. in Mathematics, Minor in Economics, Massachusetts Institute of Technology, 2007

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- **Academic Appointments**

Assistant Professor of Finance, McCombs School of Business, The University of Texas at Austin, 2012-Present

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Information and frictions in financial markets, return predictability, asset management, derivative securities

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◻ Education

He holds an MA in economics from Cornell University
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Prior to completing his PhD, So worked as a research analyst at the Nasdaq Stock Market in the Economic Research department.

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His research interests include equity valuation, asset pricing, option markets, security analysts, and limits to arbitrage with a focus on the forces and mechanisms that shape the information content of market prices.

Abstract

- We develop and implement a new measure of information asymmetry among traders. Our measure is based on the intuition that informed traders are more likely than uninformed traders to generate abnormal volume in options or stock markets.
- We formalize this intuition theoretically and compute the resulting multimarket information asymmetry measure (MIA) for firm-days as a function of unsigned volume totals and without estimating a structural model.
- Empirically, MIA has many desirable properties:

it is positively correlated with spreads, price impact, and absolut order imbalances; predicts future volatility; is an effective conditioning variable for trading strategies stemming from price pressure; and detects exogenous shocks to information asymmetry.

Background

An important variable in most theoretical and empirical work on information economics in financial markets is the fraction of volume originating from informed traders.

alternative proxies for information asymmetry among traders

alternative proxy	example	advantages	disadvantages
simple characteristics of the stock	firm size, analyst coverage	easy to calculate intuitively correlated with information asymmetry	noisy , difficult to interpret
structural estimates of model parameters.	PIN	a theoretical connection to information asymmetry; not confounded by liquidity or cash flows	computationally intensive

Duarte et al. (2015) show that measures based on estimates of order imbalances alone, including PIN, are ineffective and note that "a different approach involving variables other than order flow is necessary to generate useful inferences about the arrival of informed trade"

Our approach responds to this call by leveraging the dispersion of trades across options and stock markets.

Compare to PIN, MIA 's advantages:

- using volume imbalances across markets
- does not require estimating a structural model
- MIA can be estimated at the daily level
- MIA extends the scope of the analysis to measure informed trade across multiple markets.

1. Introduction

Our multimarket information asymmetry measure, MIA, is a simple function of unsigned volume totals based on the idea that informed traders face a leverage constraint that generates a trade-off between smaller price impact in equity markets and additional leverage in options markets.

$$\mathrm{MIA}_{j,t} = \frac{|O_{j,t}/S_{j,t} - M_{j,t}|}{O_{j,t}/S_{j,t} + M_{j,t}}, \qquad (1)$$

where $M_{j,t}$ is an estimate of average O/S in the absence of informed trade.

The main work

MIA

- Model
  - a baseline model: a constant fraction of uninformed trade
    - informed trading volume is concentrated entirely in either options or stock markets
  - extended model: strategic trading(a leverage constraint)
    - a random fraction of uninformed trading volume
- Empirical Tests
  - associations: bid-ask spreads, price impact, and absolute order imbalances.
  - predictions: future volatility incremental to contemporaneous volumes and volatilities
    - volatility incremental to option-implied volatility
  - conditioning: the returns of a daily reversal strategy
    - the returns of implied-volatility-spread trading strategy
- additional analyses
  - information events: earnings announcements and 8-K filings
  - exogenous shocks: terminations of analyst coverage

contribution

- The central contribution of this paper is the development of a new proxy for information asymmetry among traders that leverages how trades are dispersed across equity and options markets.
- An important contribution of our paper is to show that information asymmetry is better measured by absolute changes in O/S, rather than levels or signed changes of O/S.
- Another related use of levels and signed changes in O/S are as proxies for the sign rather than magnitude of private information.

3. Model and Empirical Predictions

$$\mathrm{MIA}_{j,t} = \frac{|O_{j,t}/S_{j,t} - M_{j,t}|}{O_{j,t}/S_{j,t} + M_{j,t}}, \tag{2}$$

$M_{j,\,t}$ is the median value of O/S for firm j.

（1） Baseline Model: Ideal Conditions

$$S_t = S_{i,t} + S_{u,t}, \tag{3}$$

$$O_t = O_{i,t} + O_{u,t}. \tag{4}$$

$$u_t \equiv \frac{O_{u,t}}{O_{u,t} + S_{u,t}}, \tag{5}$$

$$i_t \equiv \frac{O_{i,t}}{O_{i,t} + S_{i,t}}. \tag{6}$$

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$$\theta_t \equiv \frac{O_{i,t} + S_{i,t} \cdot M}{O_t + S_t \cdot M}, \qquad (7)$$

Theorem 1. *If informed traders use options or stock markets exclusively ($i_t = \{0 \text{ or } 1\}$), a constant fraction of uninformed traders use options ($u_t = \bar{u}$), and $M = \bar{u}/(1-\bar{u})$, then MIA exactly equals the fraction of trades that are informed θ_t.*

informed traders using options

$$\mathrm{MIA}_t \equiv \frac{|O_t - S_t \cdot M|}{O_t + S_t \cdot M} = \frac{|O_{i,t} + V_{u,t} \cdot \bar{u} - V_{u,t} \cdot (1-\bar{u}) \cdot M|}{O_t + S_t \cdot M}$$
$$= \frac{O_{i,t}}{O_t + S_t \cdot M} = \theta_t, \qquad (8)$$

informed traders using stock

$$\mathrm{MIA}_t \equiv \frac{|O_t - S_t \cdot M|}{O_t + S_t \cdot M}$$
$$= \frac{|V_{u,t} \cdot \bar{u} - V_{u,t} \cdot (1-\bar{u}) \cdot M - S_{i,t} \cdot M|}{O_t + S_t \cdot M}$$
$$= \frac{S_{i,t} \cdot M}{O_t + S_t \cdot M} = \theta_t. \qquad (9)$$

(2)Extended Model: Strategic Trading

Assumptions: u_t fluctuates over time and i_t is often between 0 and 1.

Like Back (1993), our model allow strategic trading in options as well as the underlying stock.The key addition we make to the Back (1993) model is a margin requirement, or equivalently a leverage constraint, limiting the position sizes of the informed trader.

- Model Setup

Trading occurs at time t = 0 between three types of agents: market makers, uninformed traders, and informed traders.

The informed trader chooses optimal demands $y_i \equiv (y_s, y_c, y_p)$ to maximize expected profits subject to the margin constraint.

$$m(y_i) \equiv |y_s| + \lambda(|y_c| + |y_p|) \leq \bar{m}, \qquad (12)$$

$$y_i(v) = \underset{y \text{ s.t. } m(y) \leq \bar{m}}{\arg\max}\; y_s(v - \mathbb{E}(\tilde{s}_0)) + y_c((v - \bar{v})^+ - \mathbb{E}(\tilde{c}_0)) + y_p((\bar{v} - v)^+ - \mathbb{E}(\tilde{p}_0)), \qquad (13)$$

In choosing their demand $y_i(v)$, the informed trader takes into account the impact of their demand on expected prices.They compute these expected prices based on the equilibrium pricing functions market makers use and the distribution of possible uninformed trader demands.

$$s(x_s) = \mathbb{E}(\tilde{v} \mid y_s(\tilde{v}) + \tilde{z}_s = x_s), \tag{14}$$

$$c(x_c) = \mathbb{E}(\tilde{c} \mid y_c(\tilde{v}) + \tilde{z}_c = x_c), \tag{15}$$

$$p(x_p) = \mathbb{E}(\tilde{p} \mid y_p(\tilde{v}) + \tilde{z}_p = x_p). \tag{16}$$

- Model Equilibrium

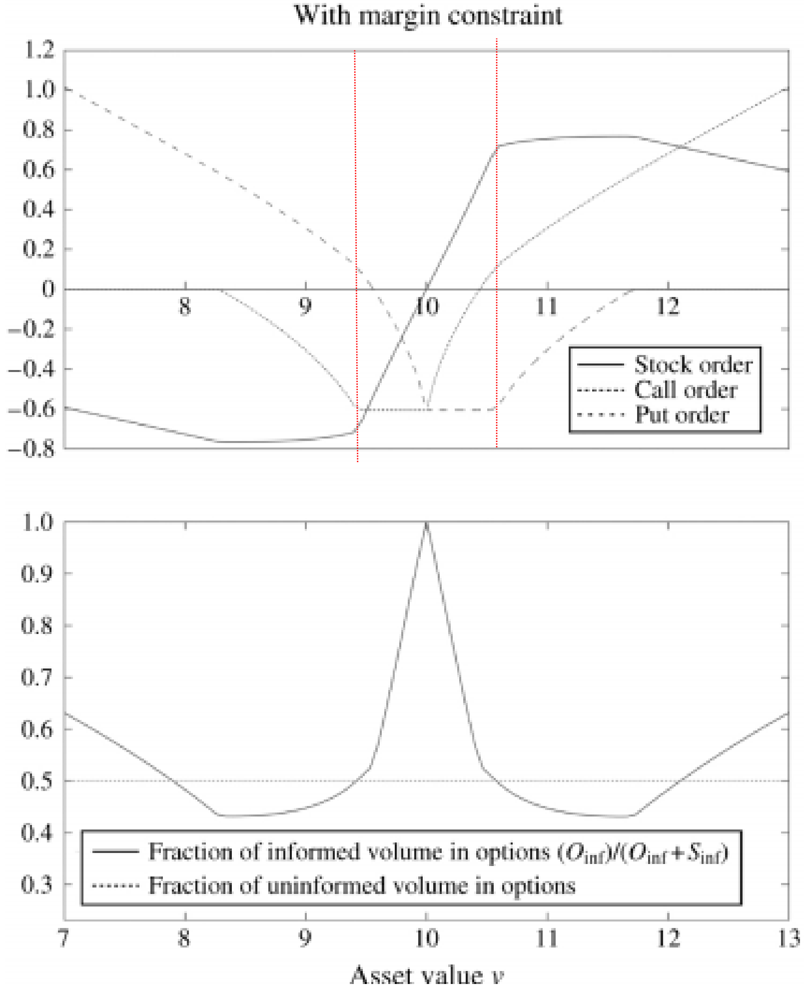
The nonlinearity of both the options' payoffs and the margin constraint prevent us from deriving a closed-form solution. Instead, we solve the model numerically for a variety of parameter values given in panel A of Table 1.

Table 1. Model Parameters and Simulations

Panel A: Parameter values		
Parameter	Description	Value
$\bar{v}$	Average stock value	10
σ_v	Standard deviation of stock value	1
$\sigma_{z,s}$	Standard deviation of uninformed of stock demand	1
$\sigma_{z,c}$	Standard deviation of uninformed call demand	0.5
$\sigma_{z,p}$	Standard deviation of uninformed put demand	0.5
λ	Margin requirement for options relative to shares of stock	0.4
$\bar{m}$	Margin constraint in number of shares	1
ϕ	Probability there is an informed trader	25%, 50%, 75%, or 100%
σ_u	Standard deviation of fraction of uninformed volume in options	0%, 1%, 2%, or 5%
$\bar{u}$	Average fraction of uninformed volume in options	50%
V_u	Total volume of uninformed traders	3 or 6

Figure 1. Equilibrium Informed Trader Demand in the Model $\bar{m} = 1$

$\bar{m} = \infty$.



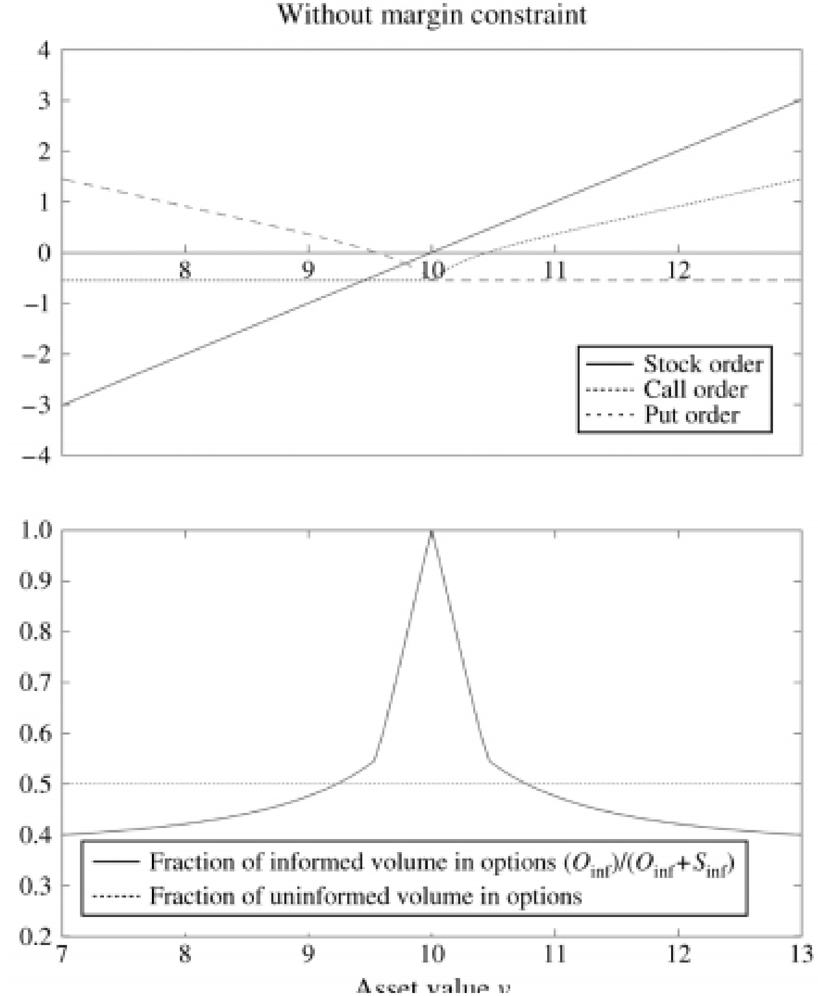
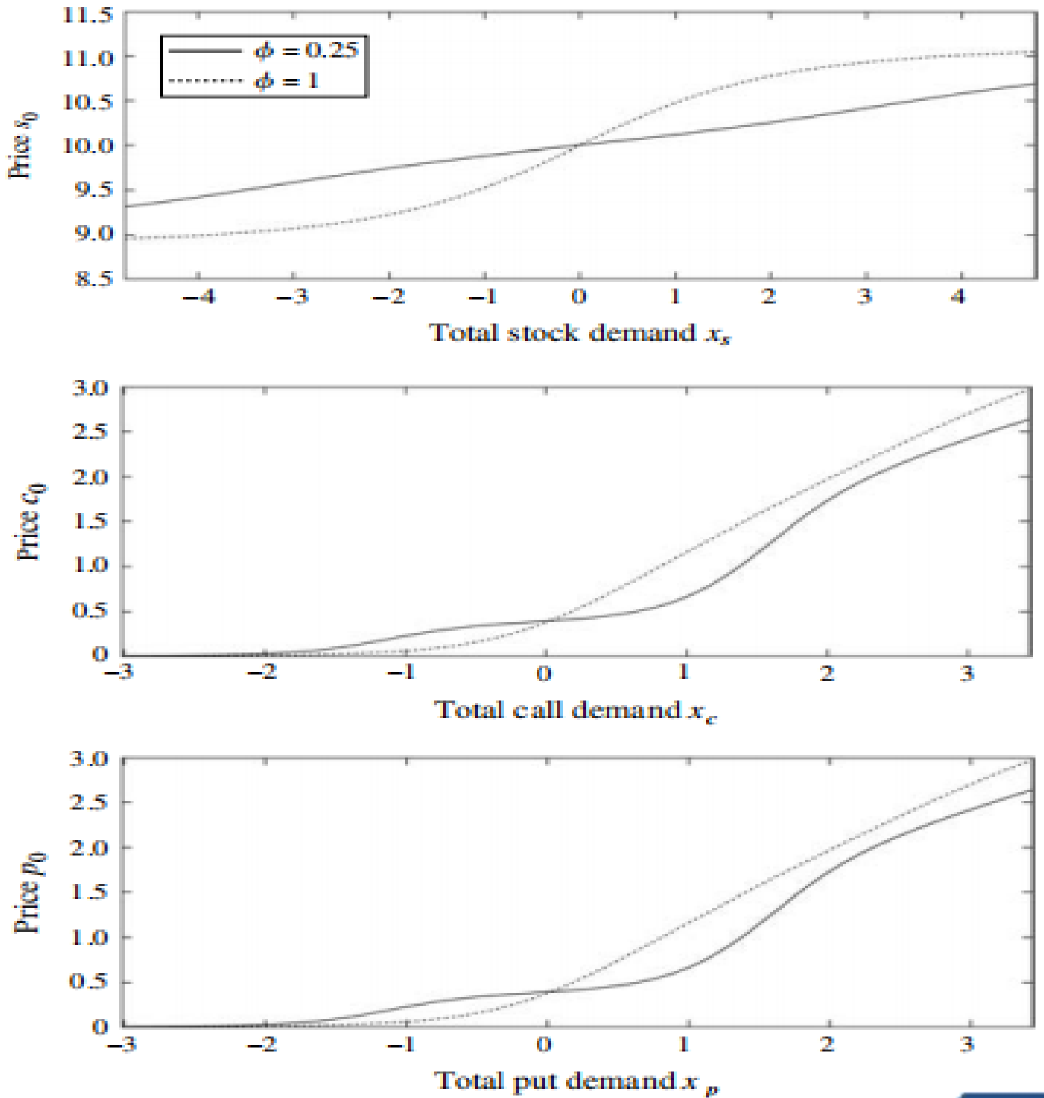


Figure 2. Equilibrium Price Functions in the Model



Simulations(which parameter choices determine the effectiveness of MIA)

We hypothesize that abnormal O/S indicates informed trade, making MIA an effective measure, as long as the fraction of uninformed trading volume in options markets is less volatile than the fraction of informed volume.

$$O_{u} = V_{u} \cdot \tilde{u}, \tag{17}$$

$$S_{u} = V_{u} \cdot (1 - \tilde{u}). \tag{18}$$

$$\theta_t \equiv \frac{O_{i,t} + S_{i,t} \cdot M}{O_t + S_t \cdot M} \qquad \text{MIA}_t \equiv \frac{|O_t - S_t \cdot M|}{O_t + S_t \cdot M}. \tag{19}$$

we use the cross-observation median of O/S as M.

We measure the effectiveness of MIA as a proxy for θt in two ways.

1.whether average MIA increases across simulated samples as we increase φ or decrease V_u, both of which should increase the prevalence of informed trade.

2.whether average MIA is higher within simulated samples among the observations where there is informed trade compared to the observations where there is no informed trade.

Panel B: $\sigma_u = 0\%$

	$V_u = 3$				$V_u = 6$			
ϕ	0.25	0.50	0.75	1.00	0.25	0.50	0.75	1.00
$\hat{M}$	1.000	1.000	1.000	0.996	1.000	1.000	1.000	0.998
Mean θ (%)	5.14	9.92	14.08	17.62	2.87	2.87	7.77	9.67
Mean MIA (%)	1.16	2.13	3.12	3.89	0.66	1.19	1.72	2.12
$\sigma(O/S)$ inf (%)	3.51	3.29	3.01	2.69	2.00	1.85	1.66	1.47
$\sigma(O/S)$ no inf (%)	0.00	0.00	0.00	—	0.00	0.00	0.00	—
Mean MIA inf (%)	4.65	4.26	4.16	3.89	2.63	2.39	2.29	2.12
Mean MIA no inf (%)	0.00	0.00	0.00	—	0.00	0.00	0.00	—

Panel C: $\sigma_u = 1\%$

	$V_u = 3$				$V_u = 6$			
ϕ	0.25	0.50	0.75	1.00	0.25	0.50	0.75	1.00
$\hat{M}$	1.005	1.004	1.004	1.003	1.004	1.006	1.007	1.009
Mean θ (%)	5.15	9.92	14.08	17.62	2.87	5.51	7.77	9.66
Mean MIA (%)	2.46	3.15	3.76	4.18	2.02	2.32	2.55	2.66
$\sigma(O/S)$ inf (%)	3.59	3.39	3.11	2.82	2.18	2.05	1.88	1.72
$\sigma(O/S)$ no inf (%)	1.00	1.00	1.00	—	1.00	1.00	1.00	—
Mean MIA inf (%)	5.01	4.69	4.48	4.18	3.26	3.03	2.86	2.66
Mean MIA no inf (%)	1.61	1.60	1.60	—	1.61	1.61	1.62	—

Panel D: $\sigma_u = 2\%$								
	$V_u = 3$				$V_u = 6$			
ϕ	0.25	0.50	0.75	1.00	0.25	0.50	0.75	1.00
$\hat{M}$	1.009	1.011	1.014	1.016	1.007	1.011	1.014	1.017
Mean θ (%)	5.14	9.91	14.06	17.60	2.87	5.51	7.76	9.66
Mean MIA (%)	3.85	4.32	4.69	4.88	3.47	3.63	3.70	3.69
$\sigma(O/S)$ inf (%)	3.85	3.66	3.42	3.16	2.67	2.57	2.44	2.33
$\sigma(O/S)$ no inf (%)	2.00	2.00	2.00	—	2.00	2.00	2.00	—
Mean MIA inf (%)	5.78	5.42	5.18	4.88	4.28	4.04	3.86	3.69
Mean MIA no inf (%)	3.21	3.22	3.24	—	3.20	3.22	3.25	—

Panel E: $\sigma_u = 5\%$								
	$V_u = 3$				$V_u = 6$			
ϕ	0.25	0.50	0.75	1.00	0.25	0.50	0.75	1.00
$\hat{M}$	1.016	1.024	1.031	1.034	1.011	1.017	1.021	1.022
Mean θ (%)	5.15	9.91	14.05	17.59	2.87	5.50	7.76	9.66
Mean MIA (%)	8.16	8.15	8.04	7.83	7.96	7.86	7.73	7.58
$\sigma(O/S)$ inf (%)	5.30	5.19	5.05	4.92	4.86	4.82	4.78	4.75
$\sigma(O/S)$ no inf (%)	5.00	5.00	5.00	—	5.00	5.00	5.00	—
Mean MIA inf (%)	8.60	8.26	8.03	7.83	7.86	7.72	7.63	7.58
Mean MIA no inf (%)	8.01	8.04	8.07	—	7.99	8.01	8.02	—

4.empirical tests

Sample Construction:Our final sample is dictated by the intersection of OptionMetrics, Compustat, and CRSP data.

$$\mathrm{MIA}_{j,t} = \frac{|O_{j,t}/S_{j,t} - M_{j,t}|}{O_{j,t}/S_{j,t} + M_{j,t}}, \qquad (20)$$

We use the firm's median O/S over the past six months ending 10 trading days before t as our estimate of M, assuming the median O/S occurs on a day with no private information.

Table 2. Sample Descriptive Statistics

Panel A: Sample characteristics by year

	Firms	Firm-days	%CC	MEAN	MEDIAN	SD
1996	664	74,978	0.650	0.427	0.347	0.280
1997	883	127,236	0.763	0.438	0.354	0.283
1998	1,045	146,497	0.806	0.450	0.364	0.289
1999	1,134	160,268	0.860	0.430	0.350	0.282
2000	1,380	201,137	0.838	0.443	0.356	0.288
2001	1,254	178,232	0.738	0.494	0.405	0.299
2002	1,118	168,768	0.666	0.493	0.413	0.304
2003	1,047	158,754	0.865	0.469	0.385	0.290
2004	1,215	191,111	0.800	0.464	0.388	0.291
2005	1,316	203,525	0.764	0.460	0.385	0.287
2006	1,470	236,129	0.829	0.456	0.384	0.288
2007	1,645	257,755	0.885	0.468	0.395	0.290
2008	1,656	270,077	0.778	0.485	0.407	0.300
2009	1,501	234,094	0.926	0.497	0.399	0.300
2010	1,466	243,205	0.796	0.469	0.396	0.293
2011	1,471	242,739	0.890	0.459	0.378	0.295
2012	1,361	216,386	0.907	0.466	0.379	0.293
2013	1,368	222,935	0.930	0.453	0.368	0.288
All	1,307	201,302	0.814	0.465	0.384	0.292

Panel B: Descriptive statistics across MIA quintiles

	SIZE	LBM	COV	DISP	O	S	O/S
1 (Low MIA)	15.282	0.307	12.174	0.389	316,786	3,507,197	6.294
2	15.212	0.309	11.963	0.391	283,740	3,250,548	6.199
3	15.058	0.314	11.416	0.410	211,817	2,679,653	6.090
4	14.830	0.323	10.589	0.440	153,337	2,008,917	6.565
5 (High MIA)	14.338	0.350	8.979	0.759	112,715	1,603,517	7.034
High − Low	−0.943	0.043	−3.196	0.370	−204,070	−1,903,679	0.740

Panel C: Average correlations

	MIA	SIZE	LBM	COV	DISP	O/S
MIA		−0.228	0.075	−0.142	0.064	0.005
SIZE	−0.202		−0.094	0.471	−0.220	0.129
LBM	0.083	−0.093		−0.073	0.154	−0.104
COV	−0.122	0.438	−0.073		−0.185	0.119
DISP	0.064	−0.339	0.385	−0.121		−0.014
O/S	−0.260	0.189	−0.159	0.074	−0.054	

Associations with MIA

(1) if MIA is an effective proxy for information asymmetry among traders, it should be positively related to bid-ask spreads and price impact regardless of where abnormal volume is currently concentrated..

(2) If MIA is a good proxy for information asymmetry, it should be positively associated with order imbalances.

(3)Our model predicts that equity market imbalances are more closely related to the extent of information asymmetry when informed traders concentrate a higher fraction of their volume in equity markets, making O/S smaller than M.

Table 3. Relative Spreads and Illiquidity Regressions

Dep. variable:	Equity spreads		Option spreads		ILLIQ	
	(1)	(2)	(3)	(4)	(5)	(6)
MIA	0.010***	0.010***	0.002***	0.002***	0.003***	0.002***
	(9.80)	(9.92)	(7.07)	(7.21)	(3.74)	(3.18)
Lag(−1)	0.191***	0.191***	0.412***	0.412***	0.226***	0.225***
	(31.76)	(31.67)	(91.53)	(91.53)	(107.81)	(107.28)
Lag(−2)	0.173***	0.173***	0.184***	0.184***	0.202***	0.202***
	(34.62)	(34.52)	(68.44)	(68.34)	(102.30)	(101.43)
Lag(−3)	0.159***	0.159***	0.186***	0.186***	0.189***	0.188***
	(33.95)	(33.78)	(77.10)	(77.09)	(92.40)	(92.20)
Lag(−4)	0.162***	0.162***	0.202***	0.202***	0.182***	0.182***
	(35.14)	(35.19)	(75.01)	(75.08)	(87.33)	(87.06)
VLTY	0.000***	0.000***	−0.000***	−0.000***	0.000***	0.000***
	(2.62)	(2.79)	(−5.25)	(−5.26)	(10.84)	(9.39)
SIZE	−0.007***	−0.007***	−0.000	−0.000	−0.021***	−0.021***
	(−11.21)	(−10.96)	(−0.60)	(−0.45)	(−21.11)	(−21.01)
INST	−0.013***	−0.013***	0.002***	0.002***	−0.031***	−0.030***
	(−10.02)	(−10.01)	(5.49)	(5.63)	(−17.37)	(−17.69)
COV	0.001**	0.001**	−0.001***	−0.001***	0.003***	0.003***
	(2.33)	(2.23)	(−6.28)	(−6.42)	(9.02)	(8.66)
ΔEQVOL	−0.001*	−0.001**	0.001***	0.001***	−0.014***	−0.013***
	(−1.91)	(−2.02)	(15.34)	(15.30)	(−18.85)	(−19.20)
ΔOPVOL	−0.000*	−0.000	0.000	−0.000	0.000***	0.000
	(−1.85)	(−1.07)	(0.18)	(−0.21)	(7.08)	(1.14)
O/S	—	−0.000***	—	−0.000	—	0.000***
	—	(−4.49)	—	(−0.01)	—	(10.43)
Intercept	0.148***	0.146***	0.003**	0.003**	0.349***	0.353***
	(12.61)	(12.47)	(2.11)	(1.96)	(21.54)	(21.54)
R^2 (%)	46.477	46.575	58.571	58.660	64.233	64.352

market makers decrease liquidity when adverse selection, as measured by MIA, is high.

Table 4. Absolute Order Imbalance Regressions

Dep. variable:	OIB		
	(1)	(2)	(3)
MIA	$\boxed{0.015^{***}}$	$\boxed{0.007^{***}}$	0.006^{***}
	(27.45)	(10.85)	(10.47)
MIA × D(O/S < *M*)	—	$\boxed{0.014^{***}}$	0.014^{***}
	—	(19.15)	(18.64)
D(O/S < *M*)	—	-0.002^{***}	-0.002^{***}
	—	(−5.00)	(−5.24)
OIB(−1)	0.128^{***}	0.128^{***}	0.127^{***}
	(46.93)	(46.47)	(46.38)
OIB(−2)	0.096^{***}	0.095^{***}	0.095^{***}
	(42.79)	(42.61)	(42.34)
OIB(−3)	0.088^{***}	0.087^{***}	0.087^{***}
	(42.02)	(41.65)	(41.53)
OIB(−4)	0.085^{***}	0.084^{***}	0.084^{***}
	(39.84)	(39.53)	(39.38)
VLTY	-0.001^{***}	0.001^{***}	0.001^{***}
	(−21.03)	(5.80)	(5.89)
SIZE	-0.007^{***}	−0.000	-0.000^{*}
	(−26.25)	(−1.59)	(−1.92)
INST	-0.001^{**}	-0.001^{***}	-0.001^{***}
	(−2.38)	(−20.91)	(−20.94)
COV	-0.004^{***}	-0.007^{***}	-0.007^{***}
	(−19.88)	(−25.99)	(−25.10)
ΔEQVOL	0.001^{***}	-0.004^{***}	-0.004^{***}
	(6.98)	(−20.18)	(−20.10)
ΔOPVOL	-0.000^{***}	-0.001^{**}	-0.001^{*}
	(−8.18)	(−2.00)	(−1.66)
O/S	—	—	0.000
	—	—	(0.48)
Intercept	0.198^{***}	0.198^{***}	0.198^{***}
	(33.89)	(33.71)	(33.09)
R^2 (%)	13.515	13.895	14.093

Predicting Volatility with MIA

Our next tests are based on the hypothesis that informed trade is more prevalent before periods of abnormal volatility.

(1)some traders, through the use of prediction models or privileged access to the information itself, may have foreknowledge of pending news, resulting in an increase in the number of informed traders and abnormally high future volatility when the news becomes public.

(2)controlling for the number of informed traders, higher volatility news presents a more profitable trading opportunity and will therefore increase the size of informed traders'orders.

(3) informed traders themselves create an order imbalance cascade that causes the subsequent volatility in stock prices.

All of these forces suggest that next-period returns will be more volatile when MIA is high, both when abnormal volume is concentrated in options and when it is concentrated in stocks.

Table 5. Predicting Volatility Using MIA

Panel A: Regressions of future volatility on MIA					
Dep. variable:	RETSQ(1) (1)	RETSQ(2) (2)	RETSQ(3) (3)	RETSQ(4) (4)	RETSQ(5) (5)
MIA	1.307*** (5.04)	0.815*** (3.18)	0.994*** (3.38)	1.023*** (3.63)	0.671** (2.40)
RETSQ	0.132*** (17.64)	0.083*** (9.26)	0.079*** (11.01)	0.051*** (8.47)	0.062*** (6.83)
RETSQ(−1)	0.070*** (9.11)	0.073*** (10.71)	0.052*** (9.00)	0.060*** (7.13)	0.067*** (7.21)
RETSQ(−2)	0.062*** (10.47)	0.055*** (10.19)	0.065*** (7.98)	0.074*** (7.73)	0.061*** (7.59)
RETSQ(−3)	0.047*** (9.38)	0.064*** (7.54)	0.068*** (7.28)	0.067*** (7.97)	0.044*** (7.66)
RETSQ(−4)	0.062*** (8.14)	0.067*** (7.25)	0.065*** (8.81)	0.042*** (6.45)	0.057*** (10.26)
VLTY	0.483*** (22.53)	0.501*** (21.70)	0.513*** (21.35)	0.538*** (22.18)	0.545*** (22.31)
SIZE	−0.928*** (−11.23)	−0.977*** (−12.67)	−0.991*** (−12.66)	−1.011*** (−12.66)	−1.022*** (−12.43)
INST	−1.291*** (−4.05)	−1.228*** (−3.59)	−1.297*** (−3.57)	−1.387*** (−3.86)	−1.382*** (−3.87)
COV	0.327*** (4.15)	0.263*** (3.36)	0.246*** (3.08)	0.221*** (2.69)	0.211** (2.53)
ΔEQVOL	1.730*** (9.68)	0.798*** (5.66)	0.496*** (4.60)	0.573*** (4.81)	0.299*** (2.64)
ΔOPVOL	−0.021** (−2.33)	−0.031*** (−3.22)	−0.029*** (−2.96)	−0.044*** (−3.52)	−0.041*** (−3.58)
O/S	0.057*** (5.97)	0.060*** (5.93)	0.070*** (7.21)	0.061*** (7.24)	0.065*** (7.24)
Intercept	14.609*** (11.08)	16.229*** (12.22)	16.565*** (12.27)	17.155*** (12.39)	17.526*** (12.41)
R^2 (%)	11.192	10.023	9.624	9.405	9.296

one potential concern is that these results reflect a mechanical correlation between option volume and expectations of volatility based on public information.

- we disaggregate MIA and show that it predicts volatility both when O/S increases (i.e., O/S > M) andwhen it decreases (i.e., O/S < M).

- we also control for option-implied volatility as a summary measure of expected volatility based on public information.

Table 5. (Continued)

Panel B: Regressions of future volatility on disaggregated MIA					
Volatility measure:	RETSQ(1) (1)	RETSQ(2) (2)	RETSQ(3) (3)	RETSQ(4) (4)	RETSQ(5) (5)
MIA (O/S > M)	1.613***	0.696***	0.423	0.727**	−0.290
	(4.88)	(2.66)	(1.30)	(2.33)	(−0.99)
MIA (O/S < M)	1.031***	0.714**	1.183***	1.169***	1.083***
	(3.52)	(2.38)	(3.42)	(3.51)	(3.25)
RETSQ	0.131***	0.082***	0.079***	0.050***	0.062***
	(17.45)	(9.21)	(10.96)	(8.24)	(6.82)
RETSQ(−1)	0.069***	0.073***	0.051***	0.060***	0.067***
	(8.98)	(10.67)	(8.93)	(7.09)	(7.22)
RETSQ(−2)	0.062***	0.054***	0.064***	0.074***	0.060***
	(10.41)	(10.14)	(7.93)	(7.71)	(7.61)
RETSQ(−3)	0.046***	0.064***	0.068***	0.067***	0.044***
	(9.27)	(7.52)	(7.26)	(7.96)	(7.66)
RETSQ(−4)	0.061***	0.066***	0.065***	0.042***	0.057***
	(8.14)	(7.22)	(8.81)	(6.41)	(10.24)
VLTY	0.486***	0.502***	0.512***	0.538***	0.543***
	(22.85)	(21.84)	(21.48)	(22.37)	(22.37)
SIZE	−0.925***	−0.979***	−0.995***	−1.008***	−1.023***
	(−11.20)	(−12.80)	(−12.71)	(−12.65)	(−12.46)
INST	−1.288***	−1.213***	−1.252***	−1.346***	−1.295***
	(−4.12)	(−3.61)	(−3.55)	(−3.85)	(−3.71)
COV	0.324***	0.259***	0.237***	0.214***	0.197**
	(4.21)	(3.36)	(3.02)	(2.64)	(2.41)
ΔEQVOL	1.747***	0.811***	0.496***	0.570***	0.282**
	(9.69)	(5.75)	(4.61)	(4.74)	(2.47)
ΔOPVOL	−0.032***	−0.037***	−0.028**	−0.042***	−0.031**
	(−3.20)	(−3.47)	(−2.54)	(−2.69)	(−2.37)
O/S	0.057***	0.064***	0.081***	0.067***	0.080***
	(5.64)	(6.27)	(7.73)	(7.80)	(8.29)
Intercept	14.580***	16.282***	16.646***	17.131***	17.593***
	(11.04)	(12.32)	(12.32)	(12.36)	(12.46)
R^2 (%)	11.369	10.186	9.786	9.568	9.453

To assess how much of the information in MIA about future volatility is already reflected in option prices and commonly used proxies for information asymmetry, we repeat our volatility prediction regressions with four additional independent variables.

- option-implied variance, IV
- the firm's relative spread
- Amhiud illiquidity ratio
- absolute order imbalance

Table 6. Incremental Volatility Prediction

Dep. variable:	RETSQ(1) (1)	RETSQ(2) (2)	RETSQ(3) (3)	RETSQ(4) (4)	RETSQ(5) (5)
MIA	1.065***	0.595***	0.781***	0.703***	0.465*
	(4.77)	(2.76)	(2.87)	(3.01)	(1.88)
RS	1.281	0.365	−1.138	−0.349	−0.450
	(1.18)	(0.33)	(−1.23)	(−0.26)	(−0.41)
ILLIQ	−1.808***	−1.498***	−1.181***	−1.599***	−1.119***
	(−4.33)	(−3.59)	(−2.61)	(−4.05)	(−2.61)
OIB	−3.196***	−2.221***	−1.490***	−0.903	−1.828***
	(−4.22)	(−4.55)	(−2.98)	(−1.21)	(−2.81)
O/S	−0.002	−0.003	0.003	0.003	0.004
	(−0.22)	(−0.33)	(0.36)	(0.36)	(0.41)
IV	0.878***	0.901***	0.932***	0.923***	0.857***
	(20.81)	(17.29)	(18.09)	(16.94)	(18.13)
RETSQ(0)	0.087***	0.043***	0.036***	0.021***	0.032***
	(11.09)	(5.59)	(4.02)	(3.73)	(3.46)
RETSQ(−1)	0.021***	0.022***	0.006	0.018**	0.022**
	(3.07)	(3.15)	(1.10)	(2.18)	(2.48)
RETSQ(−2)	0.014**	0.010*	0.027***	0.020**	0.011*
	(2.18)	(1.88)	(3.25)	(2.18)	(1.72)
RETSQ(−3)	0.005	0.025***	0.011	0.012*	−0.001
	(0.95)	(2.94)	(1.48)	(1.91)	(−0.13)
RETSQ(−4)	0.017**	0.016*	0.010	−0.005	0.006
	(2.23)	(1.93)	(1.64)	(−0.65)	(0.86)
VLTY	0.010	0.010	0.006	0.025	0.067**
	(0.38)	(0.29)	(0.18)	(0.70)	(2.15)
SIZE	0.045	0.060	0.075	0.003	−0.046
	(0.59)	(0.62)	(0.79)	(0.03)	(−0.51)
INST	0.496*	0.669**	0.619*	0.671**	0.641**
	(1.80)	(2.26)	(1.90)	(2.15)	(1.97)
COV	0.145*	0.074	0.063	0.003	0.033
	(1.94)	(0.92)	(0.78)	(0.04)	(0.40)
ΔEQVOL	1.215***	0.346***	0.114	0.007	−0.087
	(8.69)	(3.07)	(1.28)	(0.07)	(−0.98)
ΔOPVOL	−0.000	−0.008	−0.008	−0.016	−0.024**
	(−0.01)	(−0.63)	(−0.83)	(−1.59)	(−2.05)
Intercept	−2.250*	−1.891	−2.156	−0.703	0.310
	(−1.69)	(−1.15)	(−1.29)	(−0.45)	(0.20)
R^2 (%)	15.145	13.873	13.572	13.282	13.042

Alternative Implementations and Robustness

(1)Alternative Estimations of M

- defines $M_{j,\,t}$ as the average level of a firm's O/S in the week after the firm's most recent earnings announcement under the assumption that the public announcement resolves information asymmetry among investors.
- defines $M_{j,\,t}$ based on historically-estimated relations between O/S and firm characteristics using the empirical model.(FIA)

(2)Robustness to Alternative Implementations.

To address potential persistent cross-sectional differences, we replicates our main tests using panel regressions that include firm and year fixed effects.

Table 7. Alternative Implementations and Robustness

Dep var:	Eq. Spr.	Op. Spr.	ILLIQ	OIB	RETSQ(1)
	Panel A: Regressions using fitted MIA ("FIA")				
FIA	0.004***	0.001***	0.011***	0.002***	0.719***
	(6.05)	(5.50)	(12.74)	(6.94)	(2.87)
R^2	0.441	0.582	0.642	0.141	0.146
Controls	Yes	Yes	Yes	Yes	Yes
	Panel B: Regressions with firm and year fixed effects				
MIA	0.004***	0.003***	0.019***	0.009***	1.758***
	(8.09)	(24.73)	(11.80)	(38.88)	(9.78)
R^2	0.575	0.622	0.504	0.232	0.070
Controls	Yes	Yes	Yes	Yes	Yes
	Panel C: Regressions excluding options expiration weeks				
MIA	0.011***	0.002***	0.028***	0.016***	1.702***
	(8.59)	(6.77)	(6.48)	(22.96)	(5.70)
R^2	0.464	0.587	0.607	0.139	0.112
Controls	Yes	Yes	Yes	Yes	Yes

MIA as a Conditioning Variable

We examine whether MIA serves as an ex ante conditioning variable that helps distinguish between informed and uninformed sources of price pressure.

(1)we examine the returns of a daily reversal strategy after conditioning on MIA.

(The daily reversal strategy consists of a long position in stocks in the lowest quintile of returns on day t and a short position stocks in the highest quintile)

daily returns reverse more substantially when MIA is low because these returns are more likely to reflect price pressure from uninformed traders.

Table 8. Reversal Strategy Returns Conditioning on MIA

Panel A: Daily return reversal strategy factor loadings

	INT	MKTRF	SMB	HML	UMD	LIQ
Q1: Low MIA	0.150	0.286	0.086	−0.291	0.027	0.163
	(6.08)	(7.59)	(2.02)	−(7.17)	(1.00)	(3.88)
Q2	0.179	0.218	0.104	−0.181	0.036	0.081
	(7.38)	(5.88)	(2.50)	−(4.54)	(1.34)	(1.96)
Q3	0.131	0.244	0.054	−0.231	0.061	0.114
	(5.45)	(6.63)	(1.31)	−(5.85)	(2.28)	(2.78)
Q4	0.133	0.240	0.111	−0.233	0.040	0.131
	(5.56)	(6.55)	(2.68)	−(5.90)	(1.49)	(3.19)
Q5: High MIA	0.065	0.275	0.150	−0.200	0.017	0.158
	(2.60)	(7.20)	(3.50)	−(4.87)	(0.60)	(3.71)
High − Low MIA	0.085	0.011	−0.065	−0.091	0.011	0.005
	(3.37)	(0.29)	−(1.50)	−(2.19)	(0.38)	(0.12)

Panel B: Daily Fama–MacBeth reversal regressions

	(1)	(2)	(3)	(4)	(5)
QRET	−0.035***	−0.046***	−0.038***	−0.044***	−0.020
	(−7.20)	(−7.83)	(−6.46)	(−8.05)	(−1.19)
QRET × MIA	—	0.025***	0.024***	0.023***	0.019***
	—	(4.23)	(4.14)	(4.08)	(3.47)
MIA	0.008	−0.042**	−0.041**	−0.031**	−0.023
	(0.68)	(−2.48)	(−2.46)	(−2.12)	(−1.62)
QRET × EQVOL	—	—	−0.000***	−0.000***	−0.000***
	—	—	(−3.01)	(−2.70)	(−2.67)
EQVOL	—	—	0.000	0.000	0.000
	—	—	(1.57)	(1.58)	(1.63)
MOMEN	—	—	—	0.000	0.000
	—	—	—	(0.73)	(0.75)
SIZE	—	—	—	0.004	0.007
	—	—	—	(0.97)	(1.43)
LBM	—	—	—	−0.020	−0.020
	—	—	—	(−0.85)	(−0.86)
O/S	—	—	—	−0.001***	−0.001***
	—	—	—	(−2.73)	(−2.77)
QRET × SIZE	—	—	—	—	−0.001
	—	—	—	—	(−1.29)
Intercept	0.069***	0.089***	0.073***	0.026	−0.021
	(4.51)	(5.49)	(4.99)	(0.32)	(−0.24)
R^2 (%)	1.587	1.796	3.548	7.078	7.295

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(2) To further examine whether MIA distinguishes informed from uninformed sources of price pressure,we examines the returns to portfolios doublesorted by MIA and implied-volatility spreads.

(The IV spread strategy consists of long positions in the highest quintile and short positions in the lowest quintile of IV spread)

implied-volatility spreads are more likely to reflect directional price pressure from informed trade when information asymmetry is high.

Table 9. Implied-Volatility-Spread Strategy Returns Conditioning on MIA

	INT	MKTRF	SMB	HML	UMD	LIQ
	Panel A: Strategy factor loadings (full sample)					
Q1: Low MIA	0.058	0.010	−0.092	−0.141	0.023	0.021
	(3.33)	(0.38)	−(3.10)	−(4.94)	(1.19)	(0.71)
Q2	0.064	0.035	−0.068	−0.079	0.018	0.041
	(3.72)	(1.32)	−(2.29)	−(2.77)	(0.97)	(1.38)
Q3	0.039	0.008	−0.039	−0.151	−0.010	−0.025
	(2.25)	(0.30)	−(1.31)	−(5.35)	−(0.53)	−(0.84)
Q4	0.080	−0.027	0.001	−0.138	−0.007	−0.008
	(4.86)	−(1.09)	(0.03)	−(5.08)	−(0.36)	−(0.28)
Q5: High MIA	0.119	0.044	−0.030	−0.163	−0.015	0.074
	(7.10)	(1.71)	−(1.03)	−(5.90)	−(0.79)	(2.57)
High − Low MIA	0.062	0.034	0.063	−0.022	−0.038	0.053
	(2.59)	(0.94)	(1.53)	−(0.56)	−(1.43)	(1.30)
	Panel B: Strategy factor loadings (O/S > M subsample)					
Q1: Low MIA	0.048	−0.002	−0.101	−0.122	0.035	−0.002
	(2.02)	−(0.05)	−(2.48)	−(3.14)	(1.35)	−(0.06)
Q2	0.078	0.055	−0.016	−0.081	0.017	0.039
	(3.14)	(1.45)	−(0.38)	−(1.97)	(0.62)	(0.91)
Q3	0.035	0.000	−0.050	−0.155	−0.019	−0.002
	(1.39)	(0.01)	−(1.15)	−(3.73)	−(0.68)	−(0.05)
Q4	0.122	0.001	0.018	−0.146	−0.033	0.033
	(5.05)	(0.02)	(0.44)	−(3.65)	−(1.23)	(0.80)
Q5: High MIA	0.150	−0.012	−0.125	−0.178	−0.035	−0.022
	(4.64)	−(0.23)	−(2.24)	−(3.31)	−(0.98)	−(0.40)
High − Low MIA	0.107	−0.013	−0.027	−0.072	−0.076	−0.025
	(2.65)	−(0.22)	−(0.38)	−(1.07)	−(1.71)	−(0.36)
	Panel C: Strategy factor loadings (O/S < M subsample)					
Q1: Low MIA	0.063	0.028	−0.055	−0.146	0.008	0.053
	(2.51)	(0.73)	−(1.28)	−(3.52)	(0.30)	(1.22)
Q2	0.052	−0.007	−0.061	−0.088	0.028	0.025
	(2.15)	−(0.20)	−(1.47)	−(2.21)	(1.05)	(0.62)
Q3	0.036	0.011	0.006	−0.156	−0.008	−0.039
	(1.39)	(0.28)	(0.14)	−(3.65)	−(0.29)	−(0.88)
Q4	0.053	−0.068	−0.024	−0.073	0.024	−0.044
	(2.17)	−(1.83)	−(0.58)	−(1.84)	(0.88)	−(1.07)
Q5: High MIA	0.115	0.024	−0.002	−0.094	−0.002	0.042
	(5.21)	(0.70)	−(0.06)	−(2.59)	−(0.09)	(1.12)
High − Low MIA	0.050	−0.003	0.052	0.053	−0.009	−0.011
	(1.49)	−(0.06)	(0.91)	(0.96)	−(0.24)	−(0.18)

5. Additional Analyses

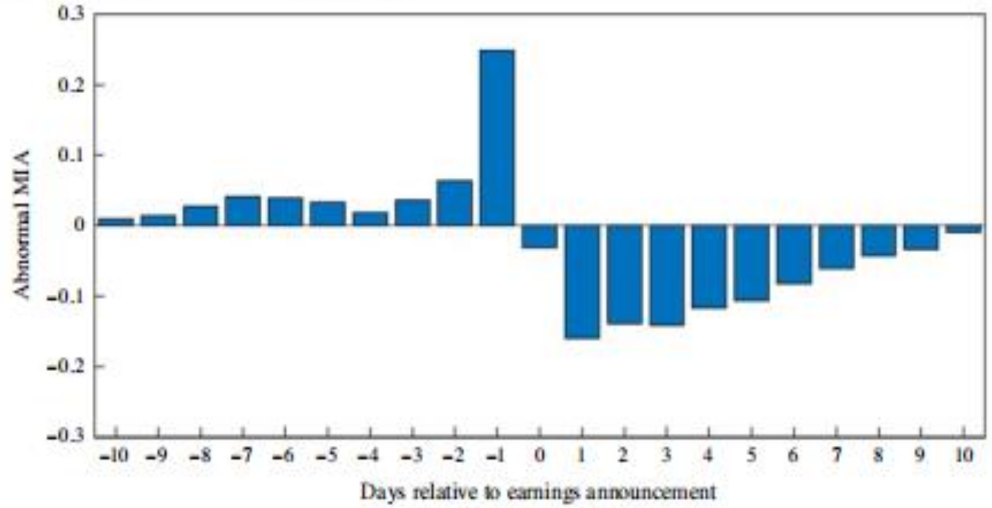
(1) Information Asymmetry Around Information Events

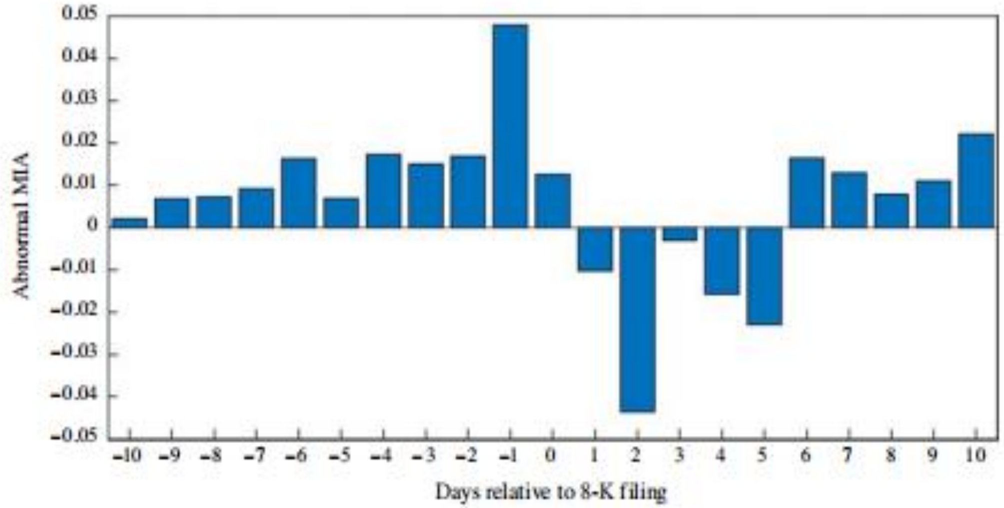
We predict that information asymmetry rises prior to information events and subsequently declines as private information is announced and becomes public.

- Earnings announcements
- 8-K filings

MIA detects informed trade even in cases in which the event is not scheduled or publicly disclosed in advance.

Figure 3. (Color online) Changes in MIA Surrounding Information Events





(2)Comparing MIA and PIN

To compare the effectiveness of PIN and MIA, Table 10 reports cross-sectional means of quarterly MIA and PIN before and after exogenous terminations of analyst coverage. We predict that MIA should rise along with information asymmetry following an exogenous reduction in analyst coverage.

- uninformed traders become less active because they rely on analysts to process information.
- informed traders' information advantages increases with the reduction in analyst coverage,resulting in more informed trading volume.

Both possibilities result in an increase in the fraction of traders with private information, and so an effective proxy for information asymmetry should increase following these exogenous shocks to analyst coverage.

Table 10. Coverage Terminations and Information Asymmetry

	Terminations		Matched controls	
	Before	After	Before	After
MIA	0.451	0.521	0.461	0.499
O/S	6.201	5.765	6.744	5.841
PIN	0.109	0.116	0.113	0.120

6. Conclusion

- MIA is positively associated with bid-ask spreads, price impact, and order imbalances, offers significant predictive power for future volatility, and distinguishes between informed and uninformed sources of price pressure.

- MIA rises before firms' earnings announcements and 8-K filing dates, and falls immediately afterward.

- MIA detects increases in information asymmetry driven by exogenous reductions in analyst coverage.

THANKS!