Frog in the Pan: Continuous Information and Momentum

Zhi Da (University of Notre Dame)

Umit G. Gurun (University of Texas at Dallas)

Mitch Warachka (Singapore Management University)

SWUFE
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Frog in the Pan

"If you put a frog in a boiling pan of water, he'll try to jump out. But if you put the the frog in a pan of cold water and gradually heat it up, the frog will sit there until he boils to death."

FIP Hypothesis: Investors are more likely to under-react to information released gradually in small pieces.

Limited Attention

- Sims (2003), Peng and Xiong (2006), and DellaVigna and Pollet (2007) provide theoretical models in which limited attention influences asset prices.
- Information needs to attract attention first before getting processed.
- The cost of processing information, as in Merton (1987), could justify the FIP hypothesis.
  - For example, emails are initially screened by their less informative headers that are less costly to process.
  - Emails containing small amounts of information may arrive frequently but receive less attention.
- Related evidence:
  - Gino and Bazerman (2009): small gradual changes induce less critical evaluation than a large sudden change.
  - Small continuous price increases in Lamb, Hair, and McDaniel (2008)
  - Large inflows into mutual funds with extraordinarily high recent returns in Daniel, Hirshleifer, and Teoh (2002)

Main Findings

- Holding past return constant, stronger price / earnings momentum when
  - the past return is archived gradually, or
  - analysts are revising consensus earnings forecasts gradually in the same direction
- This result is not driven by other well-documented predictors of price momentum
- "Continuous" past returns also predict larger consensus earnings forecast errors in the future
  - Analysts behave like "frogs in the pan"?

Other Related Literature

- **Limited Attention**
  - Hirshleifer and Teoh (2003), Barber and Odean (2008), Corwin and Coughenour (2008), Hirshleifer, Lim, and Teoh (2009), Hou, Peng, and Xiong (2009), DellaVigna and Pollet (2009), Da and Warachka (2010), Da, Gao, and Engelberg (2011), Bae and Wang (2011) among others
- **Momentum**
  - Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), Barberis, Shleifer, and Vishny (1998), Daniel, Hirsheifer, and Subrahmanyam (1998), Daniel and Titman (1999), Lee and Swaminathan (2000), Hong, Lim, and Stein (2000), Johnson (2002), Hou and Moskowitz (2005), Zhang (2006), Sagi and Seasholes (2007), Novy-Marx (2010) among others

Our Contribution

- **Limited Attention**
  - The idea of an attention lower bound complements the existing literature which has focused more the maximum amount of attention.
- **Momentum**
  - Not all momentums are created equal: those induced by continuous information and FIP do not revert in the long run.

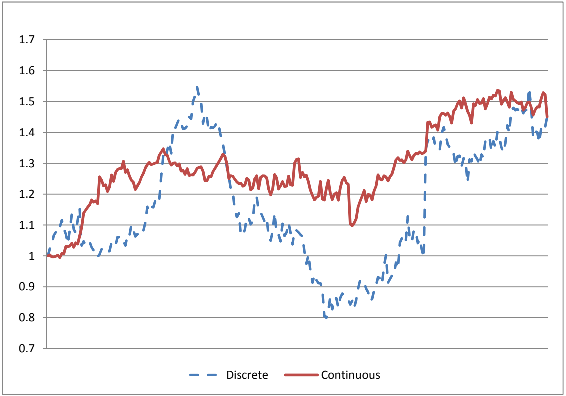
Outline

- Measure of Information Discreteness (ID)
- Information Discreteness and Momentum
  - Main results
  - Additional supporting evidence
  - Alternative explanations
- Information Discreteness and Analyst
- Illustrative Theoretical Framework
- Conclusion

Information Discreteness (ID)

- Our first proxy (ID) uses daily returns during a twelve-month formation period whose cumulative return is denoted PRET

$$\boxed{ID = sgn(PRET) \cdot [\%neg - \%pos]}$$



Information Discreteness (ID)

- A simple measure that is easy to compute, robust to outliers, can be applied to a large sample, and can be extended
- FIP hypothesis focuses on the cumulative importance of small signals, so the magnitude of a signal, as long as it is above the attention threshold, becomes irrelevant
- Unlike characteristics such as size, BM, volatility etc., ID is not persistent (autocorr $= 0.02$ at annual horizon)

Correlations

Table 1, Panel B

	ID	PRET	|PRET|	IVOL	skewness	kurtosis	jump5	jump10	DELAY	RC	UCG
ID	1										
PRET	0.163	1									
|PRET|	-0.304	0.366	1								
IVOL	0.081	-0.181	0.339	1							
skewness	0.133	0.304	0.156	0.098	1						
kurtosis	-0.008	-0.086	0.099	0.148	0.095	1					
jump5	0.242	0.245	0.266	0.127	0.147	0.208	1				
jump10	0.264	0.300	0.319	0.141	0.162	0.203	0.953	1			
DELAY	0.047	-0.063	0.041	0.253	0.093	0.107	0.064	0.069	1		
RC	-0.299	0.115	0.337	-0.056	0.005	-0.030	0.002	0.023	0.005	1	
UCG	0.056	0.685	0.100	-0.442	0.149	-0.129	0.133	0.163	-0.109	0.105	1

Double Sort: PRET first, ID second

Table 2, Panel A

Holding horizon = six months

ID	Winner 1	2	3	4	Loser 5	Avg ID	raw return	raw *t*-stat	3-factor alpha	3-factor *t*-stat
disc.	8.38	7.83	7.42	6.83	5.47	0.03	2.91	*2.10*	4.84	*5.19*
2	10.06	9.46	8.26	7.40	5.39	-0.01	4.67	*3.89*	6.46	*7.21*
3	11.52	9.80	8.63	7.44	4.80	-0.03	6.72	*5.75*	8.88	*9.30*
4	11.31	9.49	8.46	7.24	3.89	-0.06	7.42	*6.27*	9.70	*9.60*
cont.	11.08	9.12	8.38	7.15	2.22	-0.10	8.86	*6.82*	11.72	*9.70*
cont.-disc.						-0.13	5.95	*5.13*	6.89	*7.01*

Holding horizon = three years

ID	Return	t-stat	alpha	t-stat
disc.	-4.63	*-0.90*	-4.37	*-0.88*
2	1.64	*0.36*	1.95	*0.44*
3	5.89	*1.26*	6.25	*1.37*
4	3.52	*0.71*	5.28	*1.20*
cont.	8.07	*1.47*	11.77	*2.49*
cont.-disc.	12.69	*2.45*	16.20	*3.55*

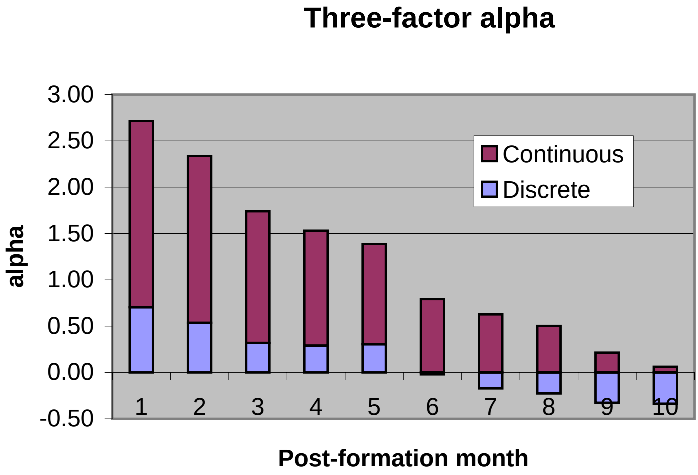
Double Sort: Stock Characteristics

Table 2, Panel B

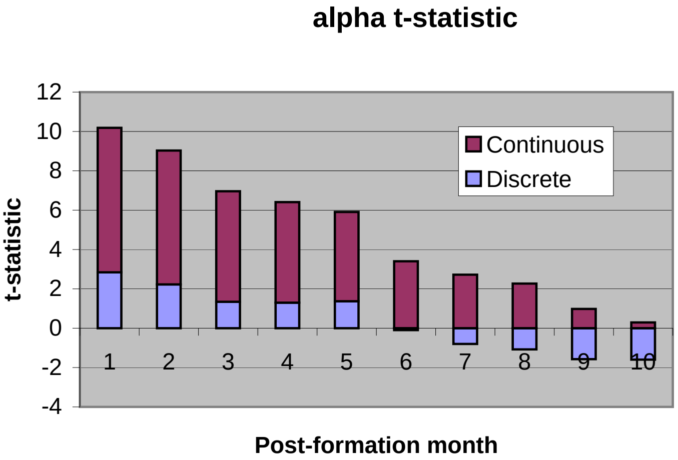
ID	ID		PRET		SIZE	
	Winner	Loser	Winner	Loser	Winner	Loser
discrete	0.03	0.01	97.82	-20.76	11.34	10.71
2	-0.02	-0.03	101.51	-23.53	11.26	10.61
3	-0.04	-0.05	108.08	-25.92	11.37	10.79
4	-0.07	-0.08	113.3	-28.98	11.64	10.97
continuous	-0.11	-0.12	129.85	-35.15	12.16	11.13

ID	BM		DISP		IVOL	
	Winner	Loser	Winner	Loser	Winner	Loser
discrete	0.52	0.71	0.04	0.08	0.54	0.29
2	0.56	0.72	0.06	0.08	0.38	0.33
3	0.55	0.73	0.05	0.10	0.32	0.33
4	0.52	0.72	0.06	0.08	0.26	0.30
continuous	0.49	0.70	0.05	0.07	0.18	0.30

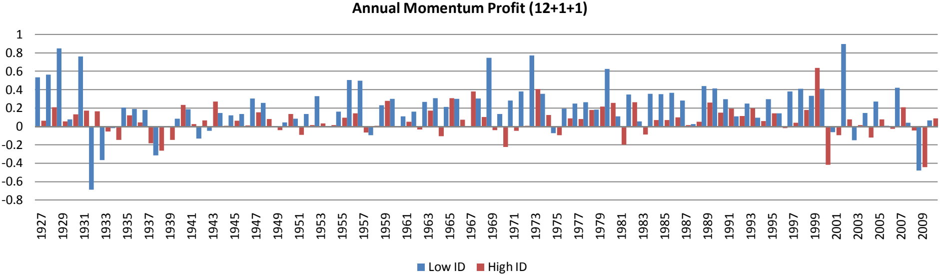
Price momentum by month



Price momentum by month



Works in Longer Sample: 1927 - 2010



Low-ID *vs.* High-ID: 21% *vs.* 6%

Results Also Robust to:

- Independent sort on ID and PRET
- Alternative formation procedure (6+1+6)
- Exclusion of NASDAQ stocks
- Exclusion of IPO stocks and distressed stocks
- Computing ID using market-adjusted returns
- ID_{HERF} that overweighs days with higher absolute returns
- ID_{Z} that accounts for zero return days

Stronger Results with Time-weighted ID

Recent returns receive more weights in computing ID

Holding horizon = six months

WID	Winner 1	2	3	4	Loser 5	Avg WID	raw Return	raw t-stat	3-factor alpha	3-factor t-stat
disc.	7.34	7.25	7.02	6.87	6.11	0.04	1.23	*0.88*	3.25	*3.65*
2	10.24	9.37	8.32	7.49	5.86	-0.01	4.38	*3.63*	6.58	*7.57*
3	10.93	9.7	8.7	7.53	4.79	-0.03	6.14	*5.18*	8.12	*8.07*
4	11.78	9.72	8.51	7.63	3.52	-0.06	8.26	*6.77*	10.52	*9.84*
cont.	12.1	9.69	8.6	6.55	1.51	-0.11	10.59	*8.68*	13.16	*11.25*
cont.-disc.						-0.15	9.36	*7.69*	9.91	7.60

Holding horizon = three years

ID	Return	t-stat	alpha	t-stat
disc.	1.38	*0.93*	3.23	*3.48*
2	3.95	*3.12*	5.93	*6.62*
3	6.21	*4.81*	8.26	*8.02*
4	7.33	*5.76*	9.49	*8.70*
cont.	10.02	*7.67*	12.64	*10.94*
cont.-disc.	8.65	*7.15*	9.41	*9.43*

Stronger Results When Institutional Investors Are Paying Less Attention

Following Hartzell and Starks (2003), we define concentration of IO as the proportion of IO accounted for by the five largest institutional investors

Table 3, Panel A

ID	Winner				Loser	Avg	raw		3-factor	
	1	2	3	4	5	ID	Return	t-stat	alpha	t-stat
				High IO Concentration						
disc.	7.88	7.01	6.28	5.94	4.55	0.14	3.33	*2.27*	6.42	*4.08*
2	9.04	7.67	6.99	6.47	4.96	0.00	4.08	*4.18*	6.80	*6.51*
3	9.68	7.74	7.38	6.50	4.33	-0.01	5.35	*4.46*	8.25	*7.42*
4	9.90	7.67	7.43	6.33	3.61	-0.04	6.29	4.53	8.99	*7.11*
cont.	10.52	7.69	7.29	6.19	1.75	-0.24	8.77	*5.59*	12.14	*7.59*
cont.-disc.						-0.38	5.44	*4.88*	5.72	*5.61*
				Low IO Concentration						
disc.	3.49	5.93	5.92	5.39	4.29	0.03	-0.80	*-0.42*	0.07	*0.05*
2	8.45	8.10	8.02	6.54	2.92	-0.01	5.53	*2.64*	9.31	*4.99*
3	9.78	9.51	8.41	7.23	1.90	-0.03	7.88	5.09	9.85	*7.30*
4	10.08	9.10	9.23	7.93	1.25	-0.05	8.83	5.08	11.30	*6.59*
cont.	9.43	10.35	10.32	7.04	-1.00	-0.09	10.43	*5.75*	11.74	*6.62*
cont.-disc.						-0.13	11.23	*4.57*	11.66	*5.59*

Stronger Results When Institutional Investors Are Paying Less Attention

Following Hartzell and Starks (2003), we define concentration of IO as the proportion of IO accounted for by the five largest institutional investors

Table 3, Panel A

ID	Winner 1	2	3	4	Loser 5	Avg ID	raw Return	raw t-stat	3-factor alpha	3-factor t-stat
High IO Concentration										
disc.	7.88	7.01	6.28	5.94	4.55	0.14	3.33	*2.27*	6.42	*4.08*
2	9.04	7.67	6.99	6.47	4.96	0.00	4.08	*4.18*	6.80	*6.51*
3	9.68	7.74	7.38	6.50	4.33	-0.01	5.35	*4.46*	8.25	*7.42*
4	9.90	7.67	7.43	6.33	3.61	-0.04	6.29	4.53	8.99	*7.11*
cont.	10.52	7.69	7.29	6.19	1.75	-0.24	8.77	*5.59*	12.14	*7.59*
cont.-disc.						-0.38	5.44	*4.88*	5.72	*5.61*
Low IO Concentration										
disc.	3.49	5.93	5.92	5.39	4.29	0.03	-0.80	*-0.42*	0.07	*0.05*
2	8.45	8.10	8.02	6.54	2.92	-0.01	5.53	*2.64*	9.31	*4.99*
3	9.78	9.51	8.41	7.23	1.90	-0.03	7.88	5.09	9.85	*7.30*
4	10.08	9.10	9.23	7.93	1.25	-0.05	8.83	5.08	11.30	*6.59*
cont.	9.43	10.35	10.32	7.04	-1.00	-0.09	10.43	*5.75*	11.74	*6.62*
cont.-disc.						-0.13	11.23	*4.57*	11.66	*5.59*

Stronger Results When Media Coverage is Low

Table 3, Panel B

ID	Winner 1	2	3	4	Loser 5	Avg ID	raw Return	raw t-stat	3-factor alpha	3-factor t-stat
High Media Coverage										
disc.	7.61	5.35	5.36	5.19	4.29	0.04	3.32	*0.63*	8.19	*2.80*
2	8.67	7.37	6.74	5.24	4.51	0.02	4.16	*1.20*	8.01	*2.89*
3	9.05	6.60	6.00	6.10	2.72	0.03	6.33	*1.90*	11.57	*3.51*
4	8.39	8.01	7.45	6.56	2.02	-0.01	6.37	*1.99*	10.95	*3.86*
cont.	10.64	8.42	7.82	5.83	0.91	-0.04	9.73	*2.85*	15.37	*4.98*
cont.-disc.							6.41	*2.19*	7.18	*2.50*
Low Media Coverage										
disc.	5.58	6.04	4.52	6.65	4.36	0.03	1.22	*0.40*	4.24	*1.62*
2	7.87	6.21	6.34	6.13	3.97	-0.01	3.90	*1.45*	7.11	*3.81*
3	10.08	8.51	7.65	6.37	4.44	-0.04	5.64	*2.00*	10.87	*4.85*
4	8.94	8.44	7.96	6.61	4.18	-0.06	4.76	*1.90*	7.07	*2.69*
cont.	10.00	9.37	7.89	6.83	0.23	-0.10	9.77	*2.87*	14.78	*5.15*
cont.-disc.							8.55	*2.47*	10.54	*3.47*

Not Driven by Return Consistency (RC)

- RC is a dummy variable equals one if a stock's monthly returns are positive (negative) for at least eight months of the annual formation period and PRET is also positive (negative)
- Grinblatt and Moskowitz (2004) show that momentum is higher when returns are consistent
- ID is a more powerful predictor of momentum than RC

Among stocks with RC=1, Table 4, Panel A

Holding horizon = six months

ID	Winner				Loser	Avg	raw		3-factor	
	1	2	3	4	5	ID	Return	t-stat	alpha	t-stat
disc.	9.24	8.39	6.02	6.36	4.05	0.02	5.19	*3.25*	6.15	*4.68*
2	10.24	9.27	8.42	7.22	4.12	-0.02	6.12	*4.49*	8.45	*7.70*
3	11.71	9.68	8.51	6.31	3.42	-0.04	8.29	*6.12*	10.93	*9.16*
4	11.76	9.44	8.18	6.59	2.54	-0.06	9.22	*7.26*	12.00	*10.80*
cont.	11.34	8.86	8.08	6.22	1.20	-0.11	10.14	*7.01*	13.42	*9.35*
cont.-disc.						-0.14	4.95	*3.55*	7.27	*4.86*

Return Consistency: Winners vs. Losers

Table 4, Panel B

	intercept	PRET	NegPRET	PosRC	NegRC	PosID	NegID	Other Controls	adj. R2
coeff	0.0541	0.0130	0.0047	0.0089	0.0034	0.1212	-0.1359	Yes	0.145
t-stat	*2.46*	*3.82*	*0.43*	*4.01*	*1.19*	*6.71*	*-6.75*		

RC only matters for past winners → Disposition effect and tax-loss selling

- Results and interpretation from Grinblatt and Moskowitz (2004).

ID affects both winners and losers → Limited Attention

- same results in the absence of control variables, and in an extended sample period from 1927.
- Control for UCG in later cross-sectional regressions to control for the disposition effect.
- ID is also defined using analyst forecast revisions although analysts are not subject to the disposition effect.

FIP vs. Disposition Effect: Horse Race in Time Series

Regress FF3-adj momentum profit following cont info on lagged proxies of attention and disposition effect

Table 3, Panel C

	Time Trend	Avg RC	UCG	AggMkt	Log(NumSt)	Abn Media	Adj. R^2
coefficient	-0.0022	-5.2956	10.2156	-3.2504	18.3517	-5.3766	0.15
t-stat	*-0.14*	*-0.73*	*1.18*	*-0.56*	*2.83*	*-2.79*	

Unlikely Driven by Return Volatility

Double Sort: PRET first, IVOL second

Table 5, Panel A

Holding horizon = six months

IVOL	Winner 1	2	3	4	Loser 5	Avg IVOL	raw Return	raw t-stat	3-factor alpha	3-factor t-stat
high	7.11	8.29	8.07	6.54	0.09	0.75	7.02	*4.14*	8.87	*6.80*
2	10.90	9.66	8.92	7.38	3.48	0.29	7.42	*5.30*	9.93	*8.62*
3	11.35	9.80	8.38	7.66	4.93	0.14	6.42	*4.73*	8.92	*8.32*
4	10.95	9.24	8.07	7.45	5.94	0.08	5.01	*4.13*	7.08	*6.90*
low	10.33	8.72	7.78	7.07	5.99	0.03	4.34	*4.26*	6.13	*7.28*
high-low						0.72	2.68	*2.07*	2.75	*2.44*

Residual ID

Controls for other well-known "predictors" of momentum using residuals

Table 6, Panel A

	intercept	$\|PRET\|$	TURN	SIZE	BM	COVER	IVOL	IO	RC	Adj. R2
coeff	-0.0248	-0.0234	-0.0043	0.0001	0.0001	-0.0010	0.0184	0.0019	-0.0336	0.1410
t-stat	*-27.81*	*-16.47*	*-4.47*	*1.06*	*0.59*	*-1.67*	*14.01*	*3.08*	*-78.50*	

Residual ID gives very similar results

Table 6, Panel B

Res	Winner				Loser	Res	raw		3-factor	
ID	1	2	3	4	5	ID	Return	t-stat	alpha	t-stat
disc.	8.50	7.89	7.46	6.82	5.31	0.06	3.19	*2.13*	5.07	*4.98*
2	10.45	9.43	8.24	7.41	5.31	0.02	5.14	*4.21*	6.58	*7.10*
3	11.12	9.77	8.62	7.46	4.79	0.00	6.33	*5.31*	8.36	*8.54*
4	11.31	9.49	8.45	7.26	3.98	-0.02	7.33	*6.01*	9.82	*8.87*
cont.	10.98	9.12	8.38	7.11	2.41	-0.07	8.57	*6.62*	11.53	*9.40*
cont.-disc.						-0.13	5.38	*3.83*	6.46	*5.70*

Cross-Sectional Regressions

Price Momentum:

$$
\begin{aligned}
r_{i,t+h} \quad = \quad & \beta_0 + \beta_1 \,\mathrm{PRET}_{i,t} + \beta_2 \,\mathrm{Res\ ID}_{i,t} + \beta_3 \,(\mathrm{Res\ ID} \cdot \mathrm{PRET})_{i,t} + \beta_4 \,\mathrm{SUE}_{i,t} \\
& + \beta_5 \,\mathrm{SIZE}_{i,t} + \beta_6 \,\mathrm{BM}_{i,t} + \beta_7 \,\mathrm{TURN}_{i,t} + \beta_8 \,\mathrm{IVOL}_{i,t} + \beta_9 \,\mathrm{AMIHUD}_{i,t} \\
& + \beta_{10} \,\mathrm{DELAY}_{i,t} + \beta_{11} \,\mathrm{UCG}_{i,t} + \beta_{12} \,(\mathrm{UCG} \cdot \mathrm{PRET})_{i,t} + \alpha X_{i,t} + \epsilon_{i,t+h}
\end{aligned}
$$

Earnings Momentum:

$$
\begin{aligned}
r_{i,t+h} \quad = \quad & \beta_0 + \beta_1 \,\mathrm{SUE}_{i,t} + \beta_2 \,\mathrm{Res\ ID}_{i,t} + \beta_3 \,(\mathrm{Res\ ID} \cdot \mathrm{SUE})_{i,t} + \beta_4 \,\mathrm{PRET}_{i,t} \\
& + \beta_5 \,\mathrm{SIZE}_{i,t} + \beta_6 \,\mathrm{BM}_{i,t} + \beta_7 \,\mathrm{TURN}_{i,t} + \beta_8 \,\mathrm{IVOL}_{i,t} + \beta_9 \,\mathrm{AMIHUD}_{i,t} \\
& + \beta_{10} \,\mathrm{DELAY}_{i,t} + \beta_{11} \,\mathrm{UCG}_{i,t} + \beta_{12} \,(\mathrm{UCG} \cdot \mathrm{PRET})_{i,t} + \alpha X_{i,t} + \epsilon_{i,t+h}
\end{aligned}
$$

Cross-Sectional Regressions

- Additional firm characteristics are included as control variables:
  1. Earnings-to-Price
  2. Total Assets
  3. Capital Expenditures to Total Assets
  4. Sales Growth
  5. Institutional Ownership
  6. Analyst Coverage
  7. Capital Gain and Its Interaction with PRET

- This list encompasses the firm-characteristics in Jegadeesh, Kim, Krische, and Lee (2004) that are documented to predict returns.

Cross-Sectional Regressions

Price Momentum: Table 6, Panel C

	intercept	PRET	Res ID	Res ID *PRET	Other Controls	adj. R2
coeff	0.0800	0.0249	0.0884	-0.2893	Yes	0.159
t-stat	*3.70*	*7.05*	*6.57*	*-9.67*		

Earnings Momentum:

	intercept	SUE	Res ID	Res ID *SUE	Other Controls	adj. R2
coeff	0.0810	0.0095	0.0706	-0.0246	Yes	0.156
t-stat	*3.74*	*3.87*	*5.30*	*-3.51*		

Analyst Forecast Errors

- Analyst earnings forecast is an important source of information in the financial market. Do analysts suffer from FIP?
- Are their earnings forecasts more prone to errors after continuous information?

Table 7, Panel A: LHS = $SURP_{i,t}$

	intercept	ID	PRET	ID*PRET	DISP	COVER	BM	SIZE	TURN	IO	adj. R2
coeff	-0.0026	0.0008	0.0020	-0.0028	-0.0011	0.0000	-0.0011	0.0003	-0.0013	0.0001	0.087
t-stat	*-3.95*	*1.22*	*7.44*	*-2.19*	*-2.64*	*-0.13*	*-3.42*	*5.32*	*-5.54*	*0.58*	

Analyst-based ID

- Our second proxy (ID_f) uses monthly earnings forecast revisions during a twelve-month formation period whose cumulative revision is denoted CUMREV

$$\boxed{ID_f = sgn(CUMREV) \cdot [\%downward - \%upward]}$$

- Replacing ID with ID_f produces similar results (Table 7, Panel B)

ID_f	Winner 1	2	3	4	Loser 5	Avg ID_f	raw Return	raw t-stat	3-factor alpha	3-factor t-stat
disc.	6.10	6.96	7.29	7.73	5.83	0.07	0.27	*0.31*	3.53	*1.91*
mid	7.41	4.32	3.59	3.13	1.45	-0.01	5.96	*3.23*	8.33	*5.11*
cont.	14.70	11.73	9.98	7.34	3.50	-0.18	11.20	*7.52*	13.66	*9.85*
cont. - disc.						-0.25	10.93	*11.02*	10.13	*6.73*

Cross-Sectional Regressions

Price Momentum: Table 7, Panel C

	intercept	PRET	ID_f	ID_f *PRET	Other Controls	adj. R2
coeff	0.0790	0.0273	0.1025	-0.1752	Yes	0.132
t-stat	*3.88*	*4.74*	*5.85*	*-2.79*		

Earnings Momentum:

	intercept	SUE	ID_f	ID_f *SUE	Other Controls	adj. R2
coeff	0.0783	0.0004	0.0590	-0.0479	Yes	0.130
t-stat	*3.83*	*0.64*	*5.63*	*-6.74*		

Illustrative Model

- Two period: $t = 0, 1, 2$
  - Stock, in zero net supply, pays a liquidating dividend at $t = 2$
  - The dividend equals the sum of two mean-zero iid signal s_1 and s_2 received at time 1 and 2 respectively
  - $P_0 = 0$ and $P_2 = s_1 + s_2$
  - s_1 is divided into N subsignals denoted s_1^i for $i = 1, \ldots, N$
- Two types of investors:
  - Rational investors process all N subsignals at $t = 1$
  - Frog-in-the-pan (FIP) investors "ignore" small subsignals ($\left|s_1^i\right| < k$)
  - As a result, expected value of the stock at $t = 1$ from the perspective of FIP investors is $s_1^{FIP} = f \cdot s_1$, with $0 < f \leq 1$ capturing the property that small subsignals are not processed
  - Both types have CARA utility
  - Proportions of FIP and rational investors are m and $1 - m$

Pricing at $t = 1$

- Computing the optimal demand for each type and setting the aggregate demand to the total supply (zero) gives us the market-clearing price P_1 at time 1

$$\begin{aligned} P_1 &= (1-m)\cdot s_1 + m \cdot s_1^{FIP} \\ &= s_1 \cdot [1 - m\cdot(1-f)] \end{aligned}$$

- Price Momentum: Approximated by covariance in price changes

$$\begin{aligned} & Cov\,(P_2 - P_1, P_1 - P_0) \\ = \;& Cov\,(s_2 + m\cdot(1-f)\cdot s_1\,,\; s_1 - m\cdot(1-f)\cdot s_1) \\ = \;& m\cdot(1-f)\cdot[1 - m\cdot(1-f)]\cdot Var(s_1) > 0 \end{aligned}$$

Illustrative Information Structure for Subsignal s_1^i

- WLOG, N subsignals s_1^i are ordered from largest to smallest in terms of their expectations

discrete	$\frac{1}{2}s_1$	$\frac{1}{2}s_1$	0	0	0	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{4}s_1$	0	0	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{8}s_1$	$\frac{1}{8}s_1$	0	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{8}s_1$	$\frac{1}{16}s_1$	$\frac{1}{16}s_1$	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{8}s_1$	$\frac{1}{16}s_1$	$\frac{1}{32}s_1$	$\frac{1}{32}s_1$	0	...	0
continuous	...								

- Holding k constant, moving from discrete to continuous information causes more subsignals to be ignored at time 1.

- Holding information structure constant, a larger k leads to more subsignals being ignored at time 1.

- Moving from discrete to continuous, more subsignals have the same sign as aggregate signal s_1.

Conclusion

We provide empirical evidence supporting a *frog-in-the-pan* hypothesis:

"Investors are less attentive to information arriving continuously in small amounts than to information with the same cumulative stock price implications arriving in large amounts at discrete timepoints."