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Business and Economics

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Deafened by Noise: Do Noise Traders Affect Volatility?

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Objectives

To investigate empirically the relation between noise traders' activities and stock price dynamics, utilizing a unique dataset from the ASX

- We test whether noise trading increases stock price volatility (Black, 1986; De Long et al., 1990)

- We also examine how the relation between noise trading activity and price volatility differs across market capitalisation

Introduction

- **Who are noise traders?**
  - Broad category of traders who trade on irrelevant information
- **Why are they important?**
  - Implications for market efficiency

Motivation I:
Does Noise Add Additional Volatility?

- Positive relation (Black, 1986; De Long et al., 1990; Andrade et al., 2008)
  - +ve relation between noise and volatility (Koski et al. 2004; Foucault et al. 2008)
  - – ve relation between noise and volatility (Verma & Verma, 2007; Kurov, 2008b)
- Negative relation – indirect route through the liquidity
  - +ve relation between liquidity and volatility (Baker & Stein, 2004; Berkman & Koch, 2008; Bloomfield et al., 2009)
  - –ve relation between liquidity and volatility (Copeland & Galai, 1983; Handa & Schwartz, 1996)

Motivation II

- Implications for investment allocation decisions
  - Suboptimal investment allocation (Dumas et al., 2009)
  - Dumas et al. (2009) argue that increased volatility, caused by irrational traders, can have a negative effect on rational traders optimal investment strategies

Motivation III

- Normative implications for policy makers
  - Important to understand whether noise traders are ‘bad’ for the market (Summers and Summers, 1989; Shleifer and Summers, 1990)
  - Understanding how to best limit their effect

What's New?

- Strong support for Black (1986) and DeLong et al. (1990)
  - We employ two direct daily proxies of noise trading
    - Dispersion in Net Initiated Order Flows - NIOF (Berkman & Koch, 2008)
    - Number of small retail transactions (Barber et al., 2009)
  - We investigate noise-volatility association using daily time series (build on tick-by-tick data)
    - Monthly and weekly data based on sentiment index (Verma & Verma, 2007; Kurov, 2008)

What Else Matters?

- How efficient are the arbitragers?
  - Cost associated with information gathering (Mitchell et al., 2002)
  - Since there are Limits to Arbitrage (Shleifer & Summers, 1990; Shleifer & Vishny, 1997)
  - Short sale constraints (Cornell & Liu, 2001; Lamont & Thaler, 2003; and Schill & Zhou, 2001)
    - Stocks without derivatives are more expensive to short (Boehme & Sorescu, 2002; Jones & Lamont, 2002)

Hence, we argue that noise traders have the greatest effect on stock price dynamics of small cap stocks

Data I

Data are from IRESS and SIRCA databases:

The initial set consists of about 1919 common stocks listed on the Australian Stock Exchange (ASX) over the sample period March 2006 – February 2008

We observe

- Date and time
- Price/quotes
- Transaction size
- Initiating broker

Data II

Filering procedure:

- Include only transactions in the continuous trading session, and exclude all crossings
- Trading day treated as day only if at least 4 different brokers initiated on that day
- Stocks that did not have qualifying trading days for at least 80% of the sample period were removed
- Preference shares, unit trusts and IPOs were removed from sample

Final sample comprises of 303

76 large cap stocks

151 medium cap stocks

76 small cap stocks

Measuring Noise Traders' Activity I

Berkman and Koch (2008)

- **Assumptions:**
  - Informed traders mimic market dispersion in NIOF across broker
    - à they have no effect on the market
  - Noise traders trade randomly
    - à an increase in the trading activity of noise traders translates into a greater dispersion in net initiated order flows across brokers

- **The standardized dispersion of net initiated order flows across brokers proxies for the level of noise trading**

Measuring Noise Traders' Activity II

Barber, Odean and Zhu (2009)

- **Assumption:**
  - Noise traders are small retail investors, who neither have the knowledge nor resources to trade in an informed manner
- **Small retail transactions defined as:**
  - Large cap stocks: volume < 300
  - Medium cap stocks: volume < 600
  - Small cap stocks: volume < 1300

Volume cut-off levels based on average bottom quartile volume, across retail transactions (Barber et al., 2009)

Noise – Volatility Relation

- $\sigma^2_t = \alpha + \theta\,\mathrm{NOISE}_t + \{\mathrm{CONTR}\} + \varepsilon_t\,,$ (1)

  - σ^2 is either:
    - Unconditional: Daily Squared Returns, Daily Range, Garman and Klass adjusted Daily Range
    - Conditional: GARCH(1,1), CGARCH(1,1)-in-mean
  - NOISE_t – measure of noise trading activity
  - CONTR: SPREAD_{t-1} (quoted spread); VOL_{t-1} (trading volume)

- **Coefficient of interest is *θ* which measures the relation between noise trading activity and daily volatility**

Noise – Volatility (Short- and Long-Run) Relation

- **We incorporate CGARCH-in-mean model**
  - Relation with two components of volatility

- Temporary component equation:

$$\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) + \theta NOISE_t + \varphi SPREAD_{t-1} + \vartheta VOL_{t-1}$$

- Permanent component equation:

$$m_t = \omega + \rho(m_{t-1} - \omega) + \gamma(\varepsilon_{t-1} - \sigma_{t-1}^2) + \theta NOISE_t + \varphi SPREAD_{t-1} + \vartheta VOL_{t-1}$$

Unconditional Volatility & Noise

$$\sigma^2_t = \alpha + q\ NOISE_t + \{CONTR\} + \varepsilon_t$$

Berkman and Koch (2008)

		α = 0.05		α = 0.10		
	Coefficient	Positive	Negative	Positive	Negative	R^2
Daily Squared Returns	0.52	64%	0%	73%	0%	7%
Daily Range	0.70	79%	0%	85%	1%	18%
Garman - Klass Range	0.77	79%	0%	83%	1%	18%

Barber, Odean and Zhu (2009)

		α = 0.05		α = 0.10		
	Coefficient	Positive	Negative	Positive	Negative	R^2
Daily Squared Returns	0.02	81%	0%	85%	0%	8%
Daily Range	0.02	92%	0%	93%	0%	18%
Garman - Klass Range	0.02	91%	0%	93%	0%	18%

Conditional Volatility & Noise Augmented GARCH(1,1)

Berkman and Koch (2008)					
		$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative
θ	0.21	68%	2%	73%	2%
$Q^2(12)$	12.21	9%		11%	
$Q^2(24)$	25.43	16%		20%	

Barber, Odean and Zhu (2009)					
		$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative
θ	0.01	63%	4%	70%	5%
$Q^2(12)$	13.53	16%		19%	
$Q^2(24)$	27.15	17%		22%	

Results – CGARCH-in-mean model

Ø Temporary component test results:

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
θ	0.20	54%	0%	64%	0%	0.01	60%	0%	66%	1%
λ	0.21	19%	4%	26%	5%	-0.01	6%	11%	8%	15%
η	-0.16	1%	19%	3%	26%	-0.13	3%	14%	6%	20%
$Q^2(12)$	10.36	6%		8%		9.56	6%		8%	

Ø Permanent component test results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
θ	0.11	27%	1%	30%	1%	0.01	30%	1%	39%	1%
λ	0.19	20%	4%	27%	5%	-0.01	5%	13%	8%	19%
η	-0.22	2%	13%	3%	21%	-0.18	2%	12%	4%	19%
$Q^2(12)$	12.43	11%		15%		10.28	9%		12%	

Results – Firm Size and Volatility

Ø Temporary component results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	θ	Positive	Negative	Positive	Negative	θ	Positive	Negative	Positive	Negative
Large Firm	0.10	47%	0%	60%	0%	0.001	53%	0%	59%	2%
Medium Firms	0.16	49%	0%	57%	0%	0.004	58%	1%	64%	1%
Small Firms	0.39	58%	0%	66%	1%	0.022	61%	0%	70%	0%

Ø Permanent component results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	θ	Positive	Negative	Positive	Negative	θ	Positive	Negative	Positive	Negative
Large Firm	0.05	23%	0%	26%	1%	0.001	27%	1%	35%	1%
Medium Firms	0.10	27%	2%	30%	2%	0.002	38%	1%	45%	1%
Small Firms	0.19	39%	0%	49%	0%	0.008	31%	0%	41%	0%

Results – Firm Size and Returns

Ø Temporary component mean equation results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	λ	Positive	Negative	Positive	Negative	λ	Positive	Negative	Positive	Negative
Large Firm	0.10	12%	6%	16%	8%	-0.009	5%	12%	6%	13%
Medium Firms	0.22	20%	3%	28%	3%	-0.023	6%	11%	9%	18%
Small Firms	0.31	23%	3%	34%	4%	0.081	8%	9%	10%	11%

Ø Permanent component mean equation results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	λ	Positive	Negative	Positive	Negative	λ	Positive	Negative	Positive	Negative
Large Firm	0.11	11%	4%	15%	7%	-0.001	2%	13%	3%	20%
Medium Firms	0.20	24%	3%	29%	4%	-0.001	4%	15%	9%	24%
Small Firms	0.28	21%	4%	33%	6%	-0.001	10%	11%	12%	11%

Robustness Tests

- We adjust the Berkman and Koch (2008) proxy for the assumption made by Barber et al. (2009)
  - Adjusted noise measure: the dispersion in NIOF across transactions initiated by retail brokers for a particular stock on a given day – results remain the same

- We perform a Durbin-Wu-Hausman test for endogeneity – there is no inverse causality

Conclusion

- **We document:**
  1) Strong evidence supporting the notion that noise traders increase daily price volatility
  2) Noise traders only affect the temporary component of price volatility

- The strongest effect is observed for small market cap firms and weakest for large market cap firms

Thank You!

Questions?