

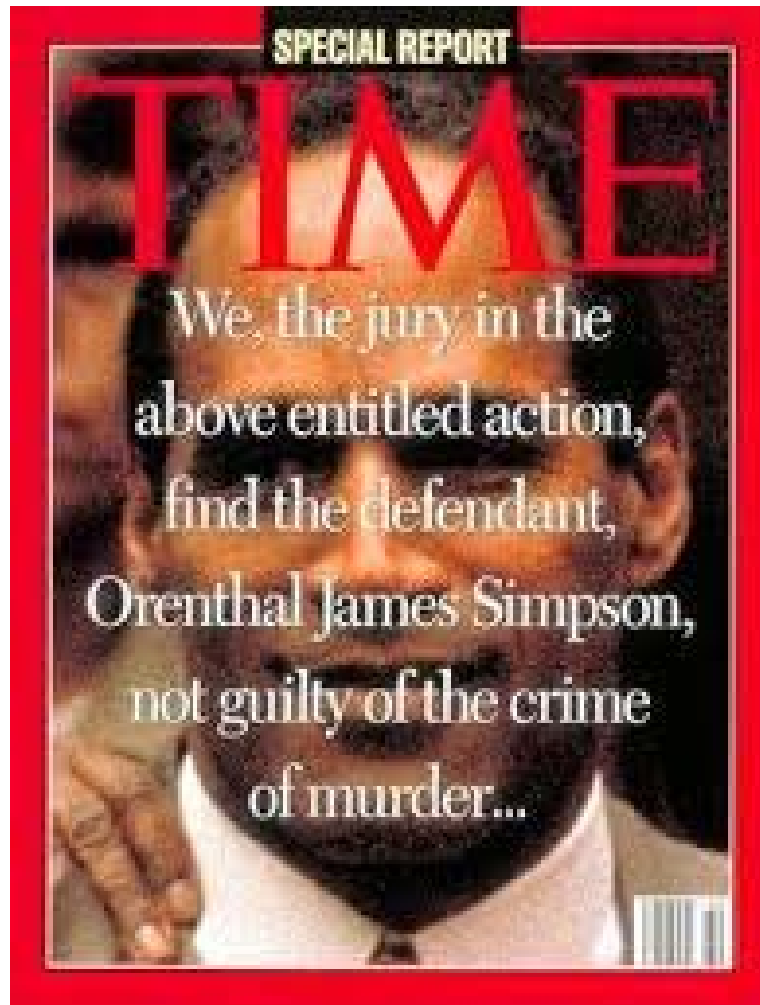
**Glued to the TV:
Distracted Noise Traders and
Stock Market Liquidity**

Joel Peress
INSEAD

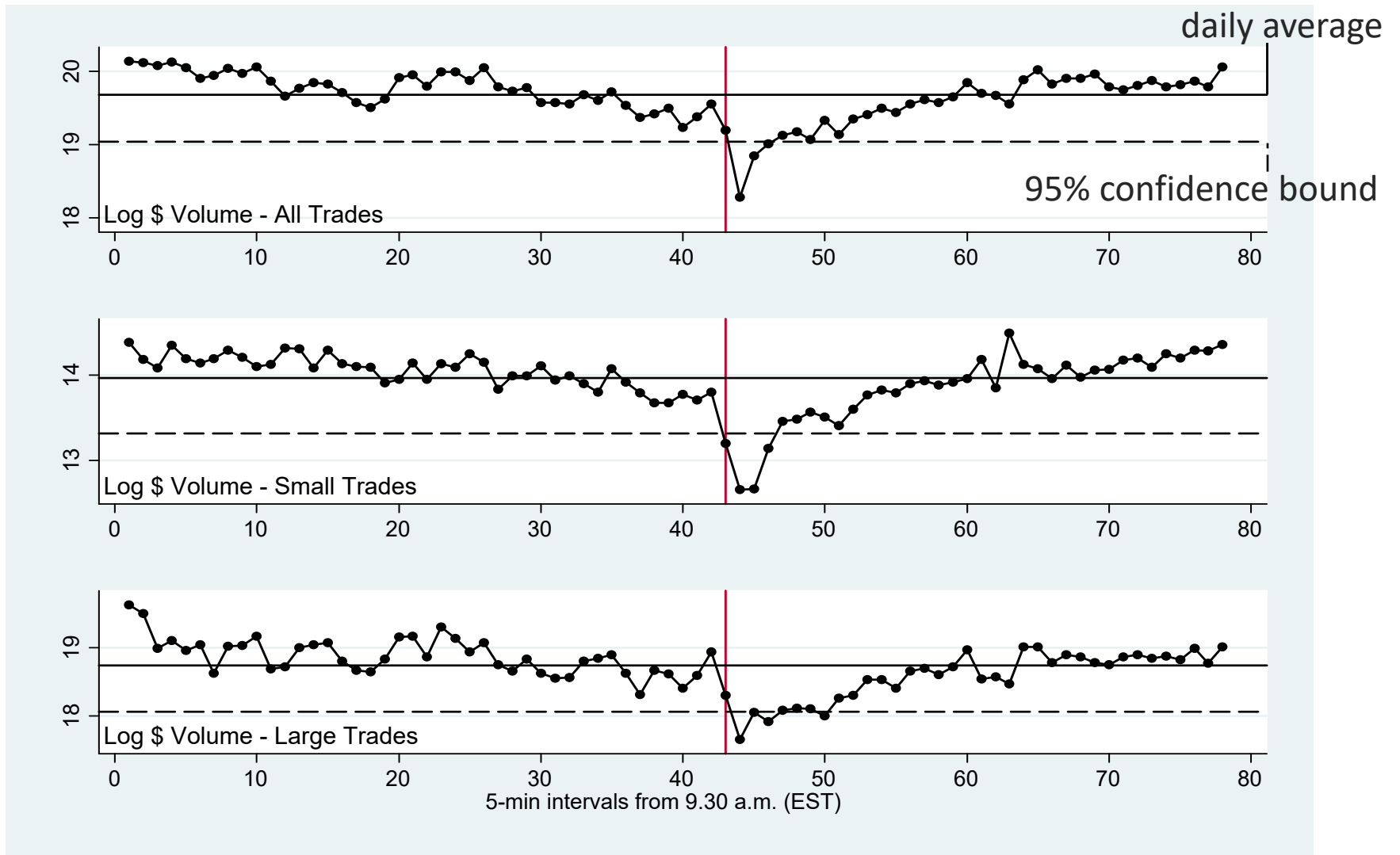
Daniel Schmidt
HEC Paris

“Trial of the Century”

- Oct. 3, 1995, 1 p.m., O.J. Simpson is declared ... not guilty!



“Trial of the Century”



What we do in this paper

1.

Sensational
(non-economic)
news events

2.

Effect on trading activity:

- Are *retail & institutional* investors distracted?
- Who is *most distractible*?
- How are *trading decisions* made?

events \approx
exogenous shocks
to noise trading

Preview of results:

- *Both* retail & institutional traders are distracted
- *More “biased” traders* are more distractible

3.

Impact of noise trader shocks on the market:

- How does the sudden withdrawal of noise traders affect *market liquidity, volatility & price reversals* ?

Preview of results:

Simultaneous reduction in trading activity, volatility, reversals & liquidity
most consistent with a (extended) model of adverse selection risk

Contributions

1. Limited attention literature:

- Focuses on speculators and market makers *DellaVigna and Pollet (2009); Hirshleifer et al. (2009); Corwin and Coughenour (2008),...*
- We study **noise traders**
- Exploits attention-grabbing events as proxied by returns, trading vol., media, Google searches... *Barber and Odean, (2008); Da et al. (2011)...*
- We use **distracting** events to mitigate concerns about confounding news

2. Determinants of liquidity literature:

- **Causal** impact of noise trading on liquidity
- Adverse selection vs. inventory management
 - Which dominates hinges on the persistence of noise trading shock
 - Permanent shock to retail trading → Inventory channel *Foucault et al. (2011)*
 - Our shocks are short-lived → **Adverse selection** channel

3. Behavioral literature:

- **Interplay** between inattention and biases *Hou et al. (2006)*

1.

Identify sensational (non-economic) news events

2.

Study effect on retail investors' trading activity

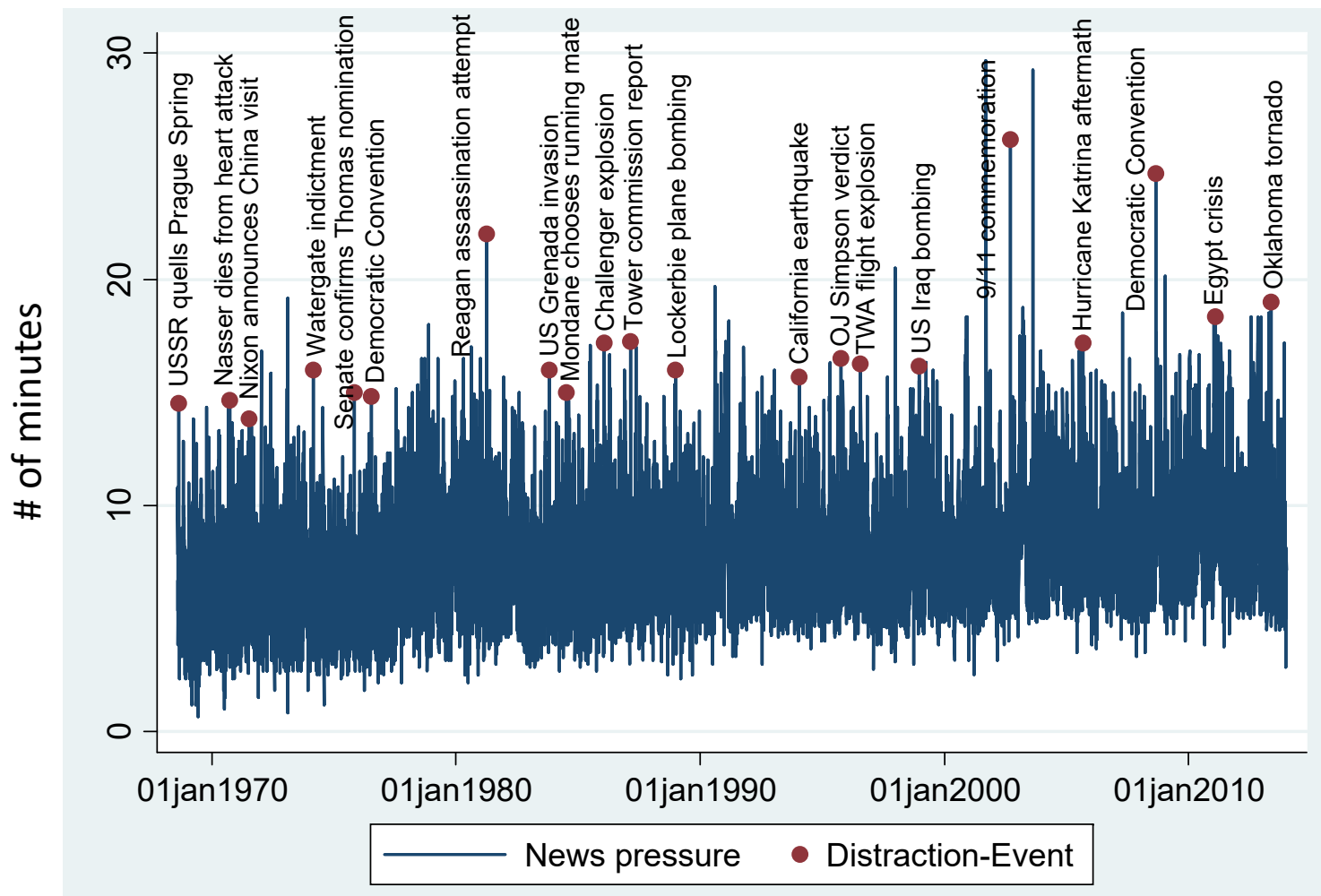
3.

Study effect on the market (noise trader shocks)

News Pressure

(Eisensee and Stromberg, QJE 2007)

- **Median time devoted to top 3 news segments** (across broadcasts)



Distraction Events

1. **Identify** events with distraction potential:
 - Focus on top decile of newspressure days for each year
 - Updated time-series over 1968-2013
 - Data includes headline information

2. **Filter out** econ. news events (attract rather than detract attention to the mkt)
 - Drop days with economic keywords in the headline (“election”, “recession”, “economy” etc)

Event Study Methodology

- **Purge** seasonal effects from all variables
 - Regress each variable on month and day-of-week fixed effects (varying by year)
- For each distraction event, calculate **abnormal** X as

$$\text{Abnormal } X = X_{t=0} - \text{Average } X_{0 < |t| < 101 \text{ \& non-economic}}$$

average over the 100 days
before and after the event

average over non-economic news
days only (using the same
economic keyword filters)

- **Inference:**

- Boehmer, Musumeci, Poulsen (1991) test
- Rank test

Abn X
(t-stat)
[z-stat]

Glued to the TV?

- TV viewership data confirm that US residents are indeed “*glued to the TV*” on distraction days
- Abnormal log average *viewership* (scaled by the number of U.S. households) over 1991-2013:
 - Daily CNN viewership
 - Evening news broadcasts viewership for ABC, CBS & NBC

CNN viewership (total day)		ABC, CBS, NBC viewership (6:30-7:00pm)	
0.339		0.031	
(12.9119)	***	(5.8892)	***
[10.3916]	***	[4.7097]	***
216		216	

Data

- **Newspressure** (*Eisensee and Strömberg, QJE 2007*) over 1968-2013

- **Trading**

- *Odean* data from “a large discount broker” over 1991-1996

- 78,000 households

- *Abel Noser Solutions (Ancerno)* over 1999–2011

- 835 Institutional traders

- *TAQ* small vs. large trades over 1991-2000

- Until 2000, small trades \approx retail trades

66 events

99 events

105 events

- **Market**

- *CRSP* over 1968-2013

532 events

- *TAQ* liquidity measures over 1993-2013

206 events

- Following Holden and Jacobsen (2014)

1.

Identify sensational (non-economic) news events

2.

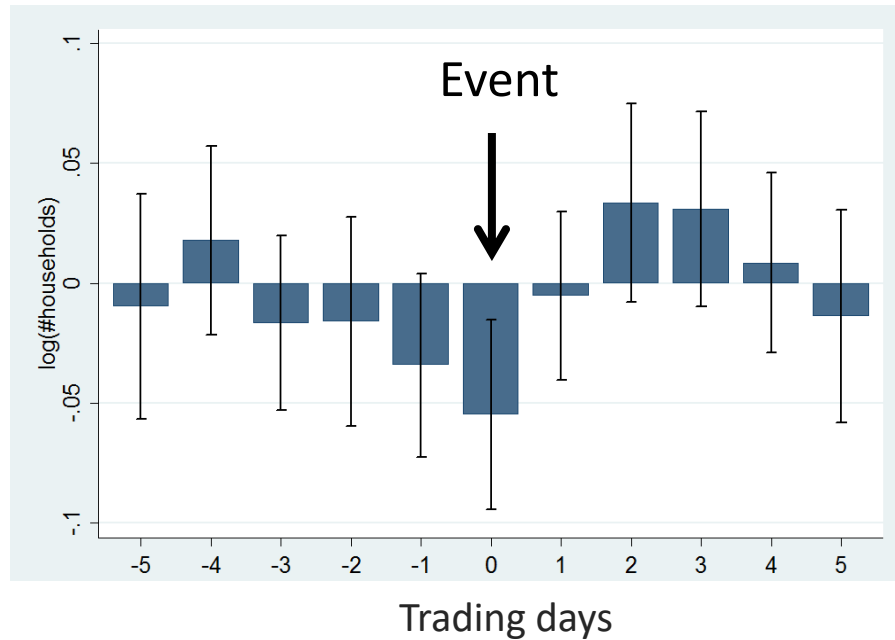
Study effect on investors' trading activity

3.

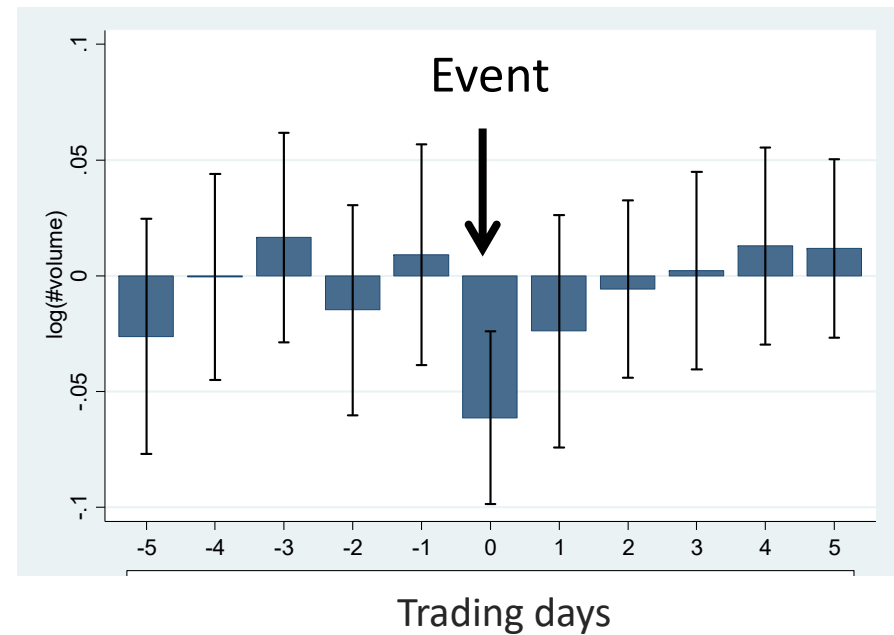
Study effect on the market (noise trader shocks)

Trading

Individuals (66 events)



Institutions (99 events)



- **Trading volume ↓ by ≈ 6%**

- Stronger for buys
- # h.h. trading ↓ by ≈ 5%

- **Trading volume ↓ by ≈ 4%**

- Symmetric between buys & sells

- No abn. trading before or after the event → No catching up of missed trades

Which Households are Most Distractable?

	Total trades		Difference
1) Gender	Single-female	Single-male	Difference
Log(#investors)	0.036	-0.093	-0.119
	-0.315	(-2.790) ***	(-2.532) **
	Low	High	Difference
2) PF concentration	-0.034	-0.066	-0.032
	(-1.778) *	(-2.671) ***	(-0.908)
3) PF volume	0.001	-0.049	-0.051
	-0.022	(-2.482) **	(-2.274) **
4) PF losses	-0.036	-0.068	-0.032
	(-1.935) *	(-2.364) **	(-0.880)
5) GK-proxy	0.001	-0.053	-0.054
	-0.016	(-2.196) **	(-2.294) **
6) Glitter-proxy	-0.0279	-0.0561	-0.0281
	(-1.328)	(-2.389) **	(-0.869)
N	66	66	66

Consistent with Barber and Odean (2001)

Overconfidence proxy based on Goetzmann and Kumar (2008) [inverse profits × turnover]

Based on stocks' media coverage [Barber and Odean (2008)]

- **“Biased” households** tend to be **more distracted**
- Given that they trade too much (Barber and Odean, 2000), retail investors **benefit from being distracted!**

Which Institutions are Most Distractable?

	Total trades		Difference
1) Gender	Single-female	Single-male	Difference
Log(\$volume)	N/A	N/A	N/A
	Low	High	Difference
2) PF concentration	-0.042	-0.049	-0.007
	(-1.447)	(-2.222) **	(-0.441)
3) PF volume	0.017	-0.043	-0.059
	-0.416	(-2.309) **	(-2.147) **
4) PF losses	-0.017	-0.056	-0.039
	(-0.923)	(-2.518) **	(-1.345)
5) GK-proxy	-0.018	-0.044	-0.025
	(-0.431)	(-2.365) **	(-1.487)
6) Glitter-proxy	-0.041	-0.062	-0.022
	(-1.686) *	(-2.350) **	(-0.950)
N	99	99	99

- **“Biased”** institutions tend to be **more distracted, like households**

TAQ Trades

- Aggregated daily \$-volume for small vs large trades for **1991-2000**
 - Over this period, trade size is a good proxy for trader type (small trades → retail vs. large trades → institutional)
 - After the decimalization in 2001, order-splitting grows → small vs. large comparison meaningless

	Small trades		Large trades		Difference	
Log(\$volume)	-0.0203		-0.0072		0.0132	
	(-1.822)	*	(-0.451)		-2.072	**
	[-2.201]	**	[-0.321]		[1.680]	*
	105		105		105	

- Significant reduction for small trades but not for large trades
 - Distractible noise traders are a larger share of retail than of institutional trading
 - **Focus on stocks with high retail ownership**

1.

Identify sensational (non-economic) news events

2.

Study effect on retail investors' trading activity

3.

Study effect on the market (noise trader shocks)

Trading Activity and Volatility by Firm Size

- Small stocks → higher retail ownership
(similar results for low-price stocks & low institutional-ownership (13F) stocks)

	N	Tercile 1	Tercile 2	Tercile 3	Difference
Log(turnover)	532	-0.024	-0.014	0.002	0.026
		(-3.174) ***	(-1.511)	-0.4049	-3.454 ***
		[-3.806] ***	[-1.857] *	[0.996]	[4.257] ***
Log(\$volume)	532	-0.028	-0.017	-0.001	0.027
		(-3.582) ***	(-1.801) *	-0.042	-3.604 ***
		[-4.138] ***	[-2.143] **	[0.593]	[4.290] ***
<i>Volatility</i>					
Abs return	532	-0.009	-0.007	0.007	0.016
		(-0.197)	-0.445	-1.603	-1.897 *
		[-1.566]	[-2.380] **	[-0.848]	[0.991]
Price range	532	-0.065	-0.016	0.011	0.076
		(-2.743) ***	-0.116	-1.922 *	-4.358 ***
		[-3.748] ***	[-1.452]	[0.768]	[4.665] ***
Intraday Volatility	206	-0.0103	-0.0053	-0.0009	0.0094
		(-3.071) ***	(-1.143)	-0.701	-3.176 ***
		[-4.209] ***	[-2.785] ***	[0.639]	[3.914] ***
Intraday Autocovari	206	0.008	0.005	0.004	-0.004
		-2.282 **	-0.071	(-0.52)	(-2.366) **
		[3.073] ***	[1.624]	[0.616]	[-1.642]

- **Trading activity, volatility & reversals ↓ among small stocks**

Liquidity by Firm Size

	<i>N</i>	Tercile 1	Tercile 2	Tercile 3	Difference
Closing bid-ask spread	335	0.061	0.012	-0.015	-0.076
		(4.171 ***	(1.622	(-0.448)	(-3.277) ***
		[3.522] ***	[1.510]	[0.124]	[-3.436] ***
Average bid-ask spread	206	0.042	-0.002	-0.021	-0.063
		(2.607 ***	(0.943	(-0.952)	(-2.229) **
		[1.377]	[-0.500]	[-1.906] *	[-1.891] *
Effective spread	206	0.043	0.014	-0.013	-0.056
		(2.301 **	(1.773 *	(0.211)	(-1.411)
		[1.803] *	[1.845] *	[-0.819]	[-2.258] **

- *Liquidity worsens (spreads ↑) among small stocks*

Liquidity by Firm Size (Cont.)

	N	Tercile 1		Tercile 2		Tercile 3		Difference	
<i>Liquidity - adverse selection</i>									
Log(amihud)	532	0.024		0.015		-0.001		-0.025	
		(3.104	***	(2.752	***	(0.331		(-2.154)	**
		[2.508]	**	[1.680]	*	[-0.748]		[-2.869]	***
Price impact	206	0.01		0.003		-0.003		-0.012	
		(1.677	*	(0.875		(-0.009)		(-1.240)	
		[1.273]		[0.109]		[-0.009]		[-1.693]	*
Absolute trade imbalance	206	0.409		0.257		-0.063		-0.472	
		(2.671	***	(2.131	**	(-0.692)		(-2.992)	***
		[2.581]	***	[1.712]	*	[-1.630]		[-2.896]	***
Lambda	206	0.009		0.004		-0.001		-0.01	
		(2.968	***	(1.899	*	(-0.450)		(-2.237)	**
		[3.288]	***	[2.414]	**	[-0.249]		[-3.372]	***
<i>Liquidity - inventory costs</i>									
Realized spread	206	0.037		0.011		-0.01		-0.047	
		(2.575	**	(1.763	*	((0.147)		(-1.854)	*
		[2.159]	**	[1.299]		[-0.698]		[-2.270]	**

Effective spread = Realized spread (<5min) + Price impact (>5min)

- **Liquidity worsens: Measures of adverse selection and of inventory costs both ↑ among small stocks**

Cross-Sectional Test

- Regressions in the cross-section of distraction events
- Ind^t variable: abnormal (log of) turnover (from CRSP)

→ Effect on trading, volatility, price reversals and liquidity are *all interconnected*

→ Driven by a *common cause*:
Reduction in noise trading

Dependent Variable	<i>N</i>	Firm Size Tercile 1
<i>Volatility</i>		
Abs. return	532	0.702 ^{***}
Price range	532	2.064 ^{***}
Intraday volatility	206	0.284 ^{***}
Intraday auto-covariance	206	-0.061 [*]
<i>Liquidity - overall</i>		
Closing bid-ask spread	335	-0.569 ^{***}
Average bid-ask spread	206	-0.695 ^{***}
Effective spread	206	-44.89 ^{***}
<i>Liquidity - adverse selection</i>		
Log(amihud)	532	-0.430 ^{***}
Price impact	206	-0.057
Absolute trade imbalance	206	-10.73 ^{***}
Lambda	206	-6.140 ^{***}
<i>Liquidity - inventory costs</i>		
Realized spread	206	-0.469 ^{***}

Two Theories of Noise Trades in Financial Markets

Adverse Selection **(Kyle; Glosten and Milgrom)**

Market makers face order flow from insiders and noise traders

Predictions for a reduction in noise:

- Lower volume
- **Higher price impact / spreads**
- [No effect on volatility]
- [No effect return autocovariance]

Inventory / Noise Trader Risk **(Stoll; Grossman and Miller; DSSW)**

Risk-averse market makers loath taking on inventory which they may not be able to unwind quickly

Predictions for a reduction in noise:

- Lower volume
- **Lower price impact / spreads**
- **Reduction in volatility**
- **Fewer reversals (higher ret. autocov.)**

- Related paper: Exploiting a *permanent* shock to retail trading, Foucault et al (2011) find evidence more consistent with the inventory channel
- But what happens for a *short-lived* shock to noise trading?

Interpretation of our Findings

- Predictions from model
 - Kyle (1985) setup (→ *adverse selection*)
 - Risk-averse mkt maker (→ *inventory risk*)
 - Short-lived distraction shock (so adverse selection > inventory risk)
- In model, distract each agent in turn:
 - *Noise traders* : std dev. of noise trades ↓
 - *Insider* : std dev. of signal error ↑
 - *Market makers* : std dev. of signal error ↑

		Trading volume	Liquidity	Return volatility	Return auto-covarianc
Who is distracted in the model?	Noise traders	Reduced	Reduced	Reduced	Increased
	Insider	Reduced	Increased	Ambiguous	Ambiguous
	Market maker	Reduced	Reduced	Increased	Reduced
What we find in the data		Reduced	Reduced	Reduced	Increased

→ Our findings are most consistent with *noise traders* being distracted

Robustness

- Sort stocks on other proxies for retail ownership (stock price, 13F Ownership data)
- Event list is robust to employing stricter or weaker filters
- Main results even hold for the list of top-10% news pressure days without economic news filters
- More checks...

Endogeneity

1. *News pressure may be high when there are economic news*

- Our economic filters should limit this problem
- We cannot rule out that some distraction events have had an economic impact, but this *should go against us!*
- Econ. news trigger more trading and volatility, the opposite of what we find

2. *News pressure may be high when there are no economic news*

- *Reverse causality*: only when the market is calm, does the media report at length about economically irrelevant news stories
- Could potentially explain our results. But:
 1. TV viewership surges on distraction days
 2. Our event study *compares high-news pressure days without econ. news to other days without econ. news*
 3. We *find nothing for the bottom-10% news pressure days* (which should then be days with lots of econ. news)

Distraction Effect over Time

- Major structural changes occurred around 2000: decimalization (2001), Reg. ATS (1998), Reg. NMS (2005), “digital revolution”, algo. trading

→ Split sample into 2 sub-periods:
1968-2000 vs 2001-2013

Impact of noise trading on **trading volume, volatility & reversals is amplified in later period** ←

	Firm Size Tercile 1		
	1968-2000	2001-2013	Difference
<i>Trading activity</i>			
Log(turnover)	-0.017	-0.048	-0.03
	(-1.96) *	(-3.65) ***	(-1.71) *
	[-2.49] **	[-3.41] ***	[-1.96] *
Log(\$volume)	-0.021	-0.051	-0.029
	(-2.42) **	(-3.54) ***	(-1.46)
	[-2.85] ***	[-3.49] ***	[-1.86] *
<i>Volatility</i>			
Abs return	0.005	-0.061	-0.067
	-0.68	(-1.58)	(-1.83) *
	[-0.69]	[-1.93] *	[-1.79] *
Price range	-0.043	-0.15	-0.107
	(-1.84) *	(-2.37) **	(-1.36)
	[-2.54] **	[-3.31] ***	[-1.84] *
Intraday volatility	-0.011	-0.029	-0.018
	(-1.68) *	(-3.74) ***	(-0.86)
	[-1.58]	[-4.21] ***	[-1.92] *
Intraday auto-covariance	0.003	0.013	0.01
	-1.24	-1.93 *	-0.48
	[1.41]	[2.89] ***	[0.93]

Distraction Effect over Time - Liquidity

	Firm Size Tercile 1		
	1968-2000	2001-2013	Difference
Closing bid-ask spread	0.077	0.03	-0.047
	-4.52 ***	-0.91	(-1.83) *
	[4.02] ***	[-0.01]	[-2.14] **
Average bid-ask spread	0.085	0.006	-0.079
	-2.7 ***	-1.03	(-1.37)
	[3.10] ***	[-0.99]	[-2.99] ***
Effective spread	0.055	0.033	-0.022
	-1.72 *	-1.56	(-0.10)
	[1.93] *	[0.60]	[-0.81]

➔ Impact of noise trading on ***liquidity is attenuated in later period***

	Firm Size Tercile 1		
	1968-2000	2001-2013	Difference
<i>Adverse selection</i>			
Log(amihud)	0.023	0.031	0.008
	-2.33 **	-2.21 **	-0.97
	[1.85] *	[1.93] *	[0.67]
Price impact	0.016	0.004	-0.012
	-2.36 **	(-0.07)	(-1.94) *
	[2.04] **	[-0.14]	[-1.52]
Absolute trade imbalance	0.485	0.346	-0.139
	-1.86 *	-1.98 *	(-0.60)
	[1.87] *	[1.78] *	[-0.25]
Lambda	0.011	0.008	-0.003
	-3.07 ***	-1.22	(-1.44)
	[2.92] ***	[1.62]	[-1.54]
<i>Inventory costs</i>			
Realized spread	0.048	0.029	-0.019
	-1.59	-2.03 **	-0.16
	[1.84] *	[1.13]	[-0.61]

Impact of Algo. Trading

- For liquidity, attenuation can be explained by *decline in retail trading*
- For volatility, reversals and trading vol., amplification might be related to the *advent of algo. trading*
 - Sort stocks by intensity of algo. trading:
 - MIDAS data: Market Information Data Analytics System
 - Combine 4 proxies into an index (Higher indicates *more* algo. trading)
 1. *Order volume-to-trade ratio*
 - total volume across all orders placed / total volume traded
 2. *Odd lot volume ratio*
 - total vol. executed in $q^{\text{ties}} < 100$ shares / total vol. traded
 3. *Cancel-to-trade ratio*
 - # of cancellations / # of trades
 4. *Average trade size*

Impact of Algo. Trading on Volume & Volatility

	Algorithmic Trading Intensity Index							
	Tercile 1		Tercile 2		Tercile 3		Difference	
<i>Trading activity</i>								
Log(turnover)	-0.037		-0.056		-0.059		-0.022	
	(-1.832)	*	(-4.009)	***	(-4.421)	***	(-2.079)	**
	[-1.887]	*	[-3.635]	***	[-4.053]	***	[-1.843]	*
Log(\$volume)	-0.044		-0.059		-0.06		-0.017	
	(-1.962)	*	(-3.825)	***	(-4.307)	***	(-1.846)	*
	[-2.07]	**	[-3.536]	***	[-4.003]	***	[-1.324]	
<i>Volatility</i>								
Abs return	-0.039		-0.076		-0.09		-0.051	
	(-1.083)		(-2.186)	**	(-2.206)	**	(-1.478)	
	[-0.848]		[-2.610]	***	[-2.352]	**	[-1.536]	
Price range	-0.08		-0.14		-0.223		-0.143	
	(-1.111)		(-2.439)	**	(-3.583)	***	(-2.669)	***
	[-1.031]		[-2.807]	***	[-4.021]	***	[-2.392]	**
Intraday volatility	-0.02		-0.027		-0.035		-0.016	
	(-2.150)	**	(-3.372)	***	(-3.749)	***	(-0.927)	
	[-2.241]	**	[-3.452]	***	[-3.699]	***	[-1.295]	
Intraday autocovariance	0.008		0.012		0.018		0.01	
	-1.157		-1.694	*	-2.379	**	-0.8	
	[1.727]	*	[1.573]		[2.293]	**	[0.589]	

→ Effect of noise trading on **volume, volatility & reversals** is stronger for stocks with more algo. trading

→ Corresponds to time-series split

Impact of Algo. Trading on Liquidity

	Algorithmic Trading Intensity Index			
	Tercile 1	Tercile 2	Tercile 3	Difference
<i>Liquidity - overall</i>				
Closing bid-ask spread	0.039	0.008	0.036	-0.003
	-1.26	(-0.074)	-1.781 *	-0.735
	[0.836]	[0.090]	[0.589]	[-0.142]
Average bid-ask spread	0.001	-0.009	0.035	0.035
	-1.055	-0.641	-1.752 *	-1.178
	[-1.524]	[-1.251]	[0.197]	[1.385]
Effective spread	0.057	0.026	0.038	-0.02
	-1.722 *	-1.414	-2.168 **	-0.626
	[1.669] *	[0.990]	[0.883]	[-0.264]
<i>Liquidity - adverse selection</i>				
Log(amihud)	0.035	0.037	0.031	-0.005
	-1.928 *	-2.045 **	-1.725 *	-0.01
	[1.983] **	[1.652] *	[0.923]	[-0.337]
Price impact	0.009	-0.011	0.001	-0.008
	-0.302	(-1.850) *	(-0.084)	(-0.308)
	[0.081]	[-2.029] **	[-0.282]	[-0.044]
Absolute trade imbalance	0.75	0.257	0.658	-0.092
	-2.933 ***	-0.916	-2.209 **	(-0.433)
	[3.141] ***	[0.827]	[2.645] ***	[-0.195]
Lambda	0.806	0.734	1.247	0.44
	-0.96	-1.127	-1.096	-0.102
	[1.176]	[1.623]	[1.019]	[0.099]
<i>Liquidity - inventory costs</i>				
Realized spread	0.041	0.038	0.034	-0.007
	-1.908 *	-2.693 ***	-1.639	-0.154
	[1.722] *	[2.206] **	[0.874]	[-0.212]

→ Impact on *liquidity weakens/doesn't vary with intensity of algo. trading*

What's Special About Algo. Trading?

- In recent period, *easier to anticipate* noise trades thanks to:
 - ***Technological advances***
 - Hardware: computing power, custom-designed chips, ultra-fast com. lines...
 - Software: pattern recognition algos, “Big Data”, A.I....
 - ***New business practices***: co-location, access to exchanges' proprietary data feeds...
- As a result easier for
 - ***Agency algos*** (asset managers) to time their informed trades
 - ***High-frequency traders*** to front-run noise trades

Conclusion

- Noise traders are distracted by sensational news ($\approx -5\%$)
 - Both *individuals* and *institutions*, but indiv. are more distractible
 - Distraction stronger for more “*biased*” investors
 - Individuals actually benefit from watching TV!
- Use sensational news to study the impact of *noise trading* in fin. markets
 - Important bc 2 theories give opposing predictions for *liquidity*:
Adverse selection vs. Inventory risk
 - Results support *adverse selection* channel:
when noise traders are out, MMs fear to trade against insiders and decrease liquidity
 - Attenuation of *volatility* & *reversals* is evidence that *inventory risk* matters (risk averse MM)
- In the age of algo. trading: Effect on *trading volume, volatility & reversals are magnified*, while *those on liquidity dampened*
 - Related to ability to anticipate noise trading

Retail Trades

- Four measures of trading intensity:

1. ***Log(\$volume)***

- Total impact on decision to trade

→ Broken up into:

2. ***Log(\$average trade size)***

- Measures ***intensive margin*** = average \$ amount per stock (conditional on trading)

3. ***Log(#stocks)***

- Measures ***intensive margin*** = # of different stocks that are traded (conditional on trading)

4. ***Log(#investors)***

- Captures ***extensive margin*** of decision to trade

Retail Trades

	Buys	Sells	Difference	Total trades
Log(\$volume)	-0.073	-0.056	-0.018	-0.065
	(-2.442) **	(-1.649)	(-0.912)	(-2.221) **
	[-2.635] ***	[-1.134]	[-0.476]	[-2.035] **
Log(avg trade size)	-0.017	-0.025	0.008	-0.019
	(-1.593)	(-1.526)	-0.111	(-1.868) *
	[-1.690] *	[-1.255]	[0.789]	[-1.664] *
Log(#stocks)	-0.01	0.003	-0.013	-0.007
	(-2.480) **	-0.841	(-2.378) **	(-2.625) **
	[-2.622] ***	[0.885]	[-2.405] **	[-2.782] ***
Log(#investors)	-0.0539	-0.0574	0.0034	-0.0508
	(-2.857) ***	(-2.061) **	(-0.714)	(-2.609) **
	[-2.693] ***	[-2.067] **	[0.214]	[-2.431] **
N	66	66	66	66

- **Trading volume ↓ by ≈ 6%** , stronger for buys
 - Propensity to trade ↓ by ≈ 5% → **strong ext. margin effect**
 - Conditional on trading, investors buy, but don't sell, fewer different stocks
→ Consistent with buys requiring more attention (*Barber and Odean, 2008*)
 - Conditional on trading, investors buy smaller q^{ties} → weak int. margin effect

Institutional Trades

	Buys	Sells	Difference	Total trades
Log(\$volume)	-0.04	-0.044	0.003	-0.042
	(-2.261)**	(-1.967)*	(-0.266)	(-2.293)**
	[-1.832]*	[-1.871]*	[0.600]	[-2.049]**
Log(avg trade size)	-0.019	-0.012	-0.007	-0.017
	(-2.014)**	(-1.211)	(-0.572)	(-2.066)**
	[-1.892]*	[-0.880]	[-0.848]	[-1.354]
Log(#stocks)	-0.014	-0.004	-0.009	-0.014
	(-1.590)	(-0.458)	(-0.858)	(-1.360)
	[-1.759]*	[-0.789]	[-1.044]	[-1.532]
Log(#investors)	-0.0026	-0.0144	0.0118	-0.0056
	(-0.385)	(-2.796)***	-2.363**	(-1.465)
	[0.436]	[-2.105]**	[2.171]**	[-0.332]
<i>N</i>	99	99	99	99

- **Trading volume ↓ by ≈ 4%**, symmetric between buys & sells
 - Conditional on trading, they buy, but don't sell, smaller quantities
 - Conditional on trading, they buy, but don't sell, fewer different stocks
 - [No reliable fund-level identifier → Caution with *Log(#investors)*]

→ ≈ Households,
but smaller
magnitude

Effect on the Overall Market

Mkt return	
-0.022	
(-0.9033)	
[-1.2294]	
532	

→ Mkt index unaffected

Log(Turnover)		Log(\$volume)	
-0.009		-0.012	
(-1.1816)		(-1.5272)	
[-1.1158]		[-1.5062]	
532		532	

→ Trading volume ↓

Abs return	Price range	Intraday volatility
-0.003	-0.013	-0.009
-1.009	-0.446	(-0.644)
[-1.575]	[-0.785]	[-1.328]
532	532	206

→ Volatility ↓

Closing bid-ask spread		Average bid-ask spread		Effective spread		Realized spread	
0.012		0		0.009		0.008	
(2.3951)	**	(1.4208)		(1.4829)		(1.7566)	*
[2.1985]	**	[0.0449]		[1.4691]		[1.3314]	
335		206		206		206	

→ Liquidity worsens
(spread in pp)

Intraday Autocovariance	
0.005	
(0.17)	
[1.879]	*
206	

→ Fewer reversals

Log(amihud)		Price impact		Absolute trade		Lambda	
0.009		0.002		0.15		0.002	
(2.6885)	***	-0.8865		(1.8913)	*	(2.0166)	**
[1.314]		[0.7185]		[1.5835]		[2.4147]	**
532		206		206		206	

Overall, weak effects

→ Focus on sub-groups of stocks predominantly held by retail investors

Distraction Events

Year	Date	Description	Year	Date	Description
1968	Aug 22	USSR invasion of Czechoslovakia	1983	Oct 25	Grenada invasion aftermath
1969	Mar 28	Eisenhower death	1984	Jul 12	Mondale chooses running mate
1970	Sep 28	Gamal Abdel Nasser death	1985	Oct 8	Achille Lauro hijacking
1971	Jul 16	Nixon announces China visit	1986	Jan 28	Challenger explosion
1972	Mar 6	Senate questions ITT settlement	1987	Feb 26	Tower commission report
1973	Jan 24	Vietnam ceasefire aftermath	1988	Dec 22	Lockerbie plane bombing
1974	Mar 1	Watergate indictments	1989	Jan 4	Libyan planes downed
1975	Nov 3	Rockefeller decides not to run for VP	1990	Aug 8	Address on Iraq's invasion of Kuwait
1976	Jul 13	Democratic Convention	1991	Oct 15	Senate confirms Thomas nomination
1977	Oct 18	West German plane hijacking	1992	May 1	Los Angeles riots
1978	Sep 19	Camp David Accords aftermath	1993	Apr 20	Waco sect compound fire
1979	Feb 14	U.S. embassy incident in Tehran	1994	Jan 17	Northridge earthquake
1980	Dec 26	Iran hostage crisis	1995	Oct 3	O. J. Simpson verdict
1981	Mar 30	Reagan assassination attempt	1996	Jul 18	TWA flight explosion
1982	Sep 20	Lebanon massacre	1997	Sep 5	Princess Diana's funeral

Kyle with Risk-Averse Market Maker

θ = final dividend x = insider's market order z = noise trades

→ total order flow: $\omega = x + z$

Market makers have CARA-utility with risk aversion γ (Subrahmanyam, 1991)

$$\rightarrow \lambda = \frac{E[\theta|\omega]}{\omega} + \frac{\gamma}{2} \text{Var}[\theta|\omega]$$

$$\rightarrow \lambda = \sqrt{\frac{\sigma_\theta}{\sigma_z}} \left(\frac{\gamma\sqrt{\sigma_\theta\sigma_z} + \sqrt{4 + \gamma^2\sigma_\theta\sigma_z}}{4} \right)$$

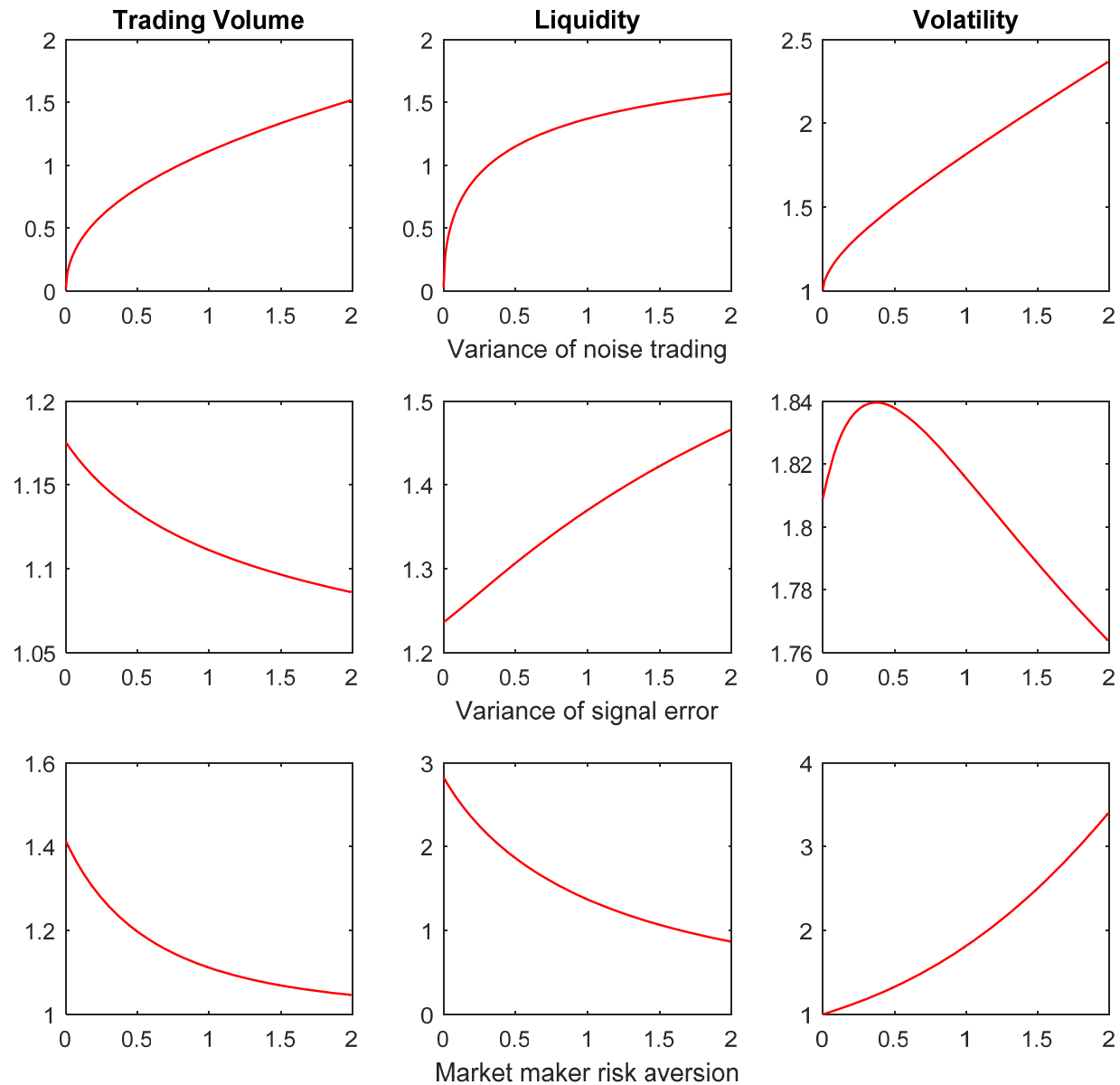
[without informed trading: $\lambda = \frac{\gamma}{2}\sigma_\theta$]

Distraction events = decrease in σ_z

Four predictions:

1. Trading volume ↓
2. Price impact λ ↑
3. Return volatility ↓
4. Return auto-covariance ↑

Are Other Agents Distracted?



Distracted Market Makers

- Increase in realized spread inconsistent with decline in noise trading but could stem from MM being distracted
- Both retail investors and professional MM supply liquidity. But prof. MM are relatively more likely to update quotes in the absence of trades

Analysis of 5-min intervals during the day (in bottom stock tercile)

	by mktcap	by price	by inst.
Fraction of 0-return intervals	0.278	0.337	0.265
	█ (2.5113) **	█ (2.819) ***	█ (2.2372) **
	[3.1093] ***	[3.484] ***	[3.135] ***
Fraction of intervals with no trade	0.273	0.408	0.331
	█ (2.637) ***	█ (3.4486) ***	█ (3.0966) ***
	[2.7941] ***	[3.8319] ***	[3.6988] ***
Fraction of 0-return intervals among intervals with no trade	0.082	0.123	0.057
	█ (1.0138)	█ (1.5174)	█ (1.058)
	[0.6578]	[1.7493] *	[0.8656]

- Fewer 0-return intervals, but not among those with no trade
 → Prof. MM don't seem to be more distracted