# Liquidity commonality and high frequency trading:

# Evidence from the French stock market

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# Motivation

**❑ Why study liquidity co-movement ?**

Co-movement or commonality in liquidity occurs when firm liquidity varies in tandem with market liquidity. $l_{i,t} = b_i^0 + b_i^1 l_{M,t} + \epsilon_{i,t}^j$

Co-movement constitutes a source of systematic illiquidity risk for portfolio managers, especially when market stress is higher: 2008 financial crisis (Nagel, 2012), 2010 Nasdaq flash crash (Kirilenko et al., 2017

**❑ Co-movement in low latency trading platforms:**

HFT algorithms react to common price shocks among securities with correlated fundamentals, generating co-movement of liquidity (Cespa and Foucault, 2014)

**❑ What is available in the literature?**

a. A lot of papers on liquidity co-movement, not assessing HFT activity
b. A lot of papers on the role of HFTs in single security liquidity

Limited papers on HFT and liquidity co-movement (a + b). Further research is needed to improve our current understanding on co-movement in liquidity supply and HFT.

# Related literature

- **HFT and liquidity supply co-movement:** Malceniece, Malcenieks, and Putnins (2019), Klein and Song (2018)

- Both studies examine the staggered entry of Chi-X in 12 European markets (difference-in-differences)
- Use of proxies of HFT activity (e.g., message/trade ratio) in daily analyses
- Collective findings: HFT increases liquidity commonality through: i) volatility and ii) process of information

- **Our research question:** Is HFT a source of liquidity supply co-movement?

- We use the BEDOFIH AMF Paris data set: HFT and DMM classification
- We investigate co-movement i) at the interday, and ii) at the intraday level
- We investigate co-movement around scheduled macro-economic news announcements

# Hypotheses

- **Liquidity co-movement**

**H1:** *Across securities*, *HFTs' liquidity supply co-moves more than NON HFTs' liquidity supply (Cespa and Foucault, 2014)*

**H2:** *Across securities, DMMs employing HFT algorithms are less diverse in their liquidity supply, as compared to other HFTs (OHFTs) (Coughenour and Saad, 2004, Brunnermeier and Pedersen, 2009)*

**H3:** *Cross-sectional co-movement in DMM, OHFT, and NON HFT liquidity increases with market stress*. *(Brunnermeier and Pedersen, 2009; Cespa and Foucault, 2014; Aït-Sahalia and Saglam; 2017a, 2017b)*

# Sample and summary statistics

- **33 CAC 40 stocks from year 2015: orders, trades, HFT, DMM classification**

Order flow:

| *ORDER FLOW* | OHFTs (%) | DMMs (%) | NON HFTs (%) |
|---|---|---|---|
| Non-marketable orders | 13.0 | 85.6 | 1.3 |
| Cancelled by member | 11.2 | 88.4 | 0.5 |
| Modified by member | 18.9 | 77.5 | 3.6 |
| Marketable orders | 29.3 | 60.1 | 10.6 |
| | | | |
| *TRADE SIZE* | Minimum | Median (50%) | 90% |
| Marketable order size (shares) | 1 | 200 | 764 |
| Trade size (shares) | 1 | 109 | 268 |

# Sample and summary statistics

- **Order book activity per trader type (DMM, OHFT, NON HFT):**

| | *Sell side* | | | *Buy side* | | |
|---|---|---|---|---|---|---|
| | HFT | | NON HFT | HFT | | NON HFT |
| LOB depth | OHFT (%) | DMM (%) | NON HFT (%) | OHFT (%) | DMM (%) | NON HFT (%) |
| Level 1 | 23.9 | 71.2 | 5.0 | 23.7 | 71.3 | 5.1 |
| Level 2 | 13.3 | 84.9 | 1.8 | 12.9 | 85.4 | 1.7 |
| Level 3 | 13.0 | 85.6 | 1.4 | 12.6 | 86.1 | 1.3 |
| Level 4 | 13.0 | 85.4 | 1.6 | 12.6 | 86.0 | 1.4 |
| Level 5 | 13.1 | 84.6 | 2.3 | 12.7 | 85.3 | 2.1 |
| Level 6 | 13.9 | 82.6 | 3.5 | 13.5 | 83.3 | 3.2 |
| Level 7 | 13.8 | 81.6 | 4.7 | 13.4 | 82.4 | 4.2 |
| Level 8 | 13.9 | 80.7 | 5.4 | 13.6 | 81.6 | 4.9 |
| Level 9 | 13.7 | 79.5 | 6.8 | 13.3 | 80.5 | 6.2 |
| Level 10 | 13.2 | 78.5 | 8.4 | 12.9 | 79.5 | 7.6 |

# Liquidity variables

- 1-min Euro/share price impact: $CT_{i,t,d}(q) = \frac{1}{q}\int_0^q [S_{i,t,d}(Q) - D_{i,t,d}(Q)]dQ\,;$

  $\text{i asset, t interval, q shares}$

- 1-min immediacy: $IM_{i,t,d} = \sum_{k=1}^{K} V_{i,k,t,d}\;;$

  $\text{k trades, t interval, V shares passively traded}$

| | DMM | OHFT | NON HFT |
|---|---|---|---|
| CT (q=1) | 0.025* | 0.039* | 0.210 |
| CT(q=200) | 0.026* ** | 0.049* ** | 0.265 ** |
| IM | 52% | 38% | 10% |

# Methodology

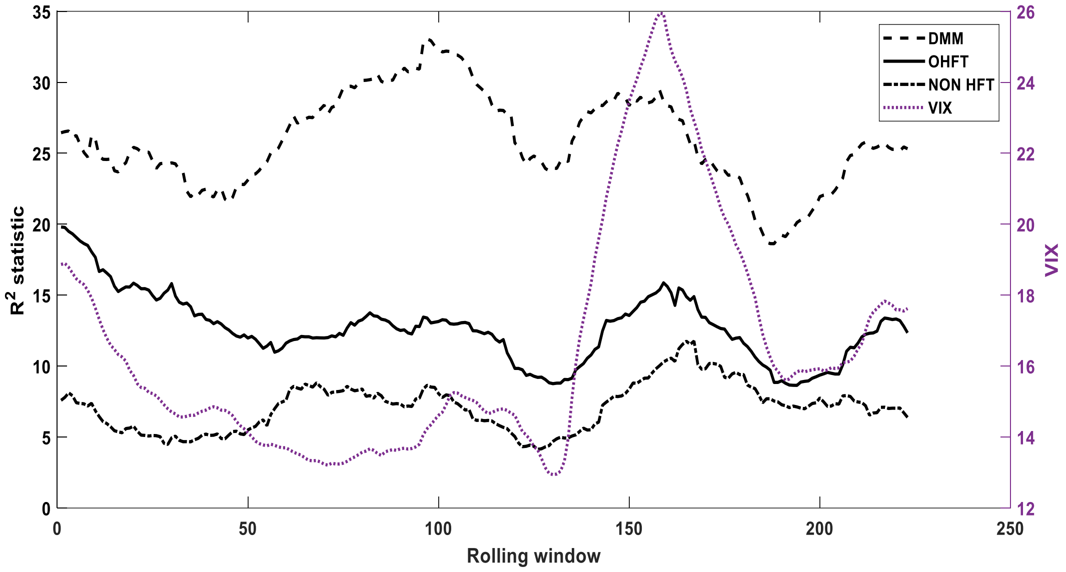
- 15-min standardized logarithmic differences : we transform l in L (differenciation and standardization)
- $L_{i,t}^{j} = A_i + B_{1,i}^{j} Vol_{i,t} + B_{2,i}^{j} Vol_{i,t-1} + B_{3,i}^{j} Vol_{i,t+1} + \Gamma_{1,i}^{j} MR_t + \Gamma_{2,i}^{j} MR_{t-1} + \Gamma_{3,i}^{j} MR_{t+1} + \omega_{i,t}^{j}, j = \{DMM, OHFT, NON\ HFT\}$ (1)
- Use $\omega_t^{i,j}$ in subsequent analysis
- PCA on liquidity series ($\epsilon_t^{i,j}$) per trader type.
- Retrieve the first principal component: $P_t^j$ as an estimation of $\omega_M$
- (for robustness, we use also the weighted traditional measure)
- $\omega_{i,t}^{j} = b_{i,j}^{0} + b_{i,j}^{1} \omega_{M,t}^{j} + b_{i,j}^{2} \omega_{M,t-1}^{j} + b_{i,j}^{3} \omega_{M,t+1}^{j} + \epsilon_{i,t}^{j}$ (2)
- $R^2$ statistic as a summary measure of co-movement (MMP, 2019)
- Robustness: cap-weighted across stock average liquidity (CRS, 2000)

# Co-movement: trader type

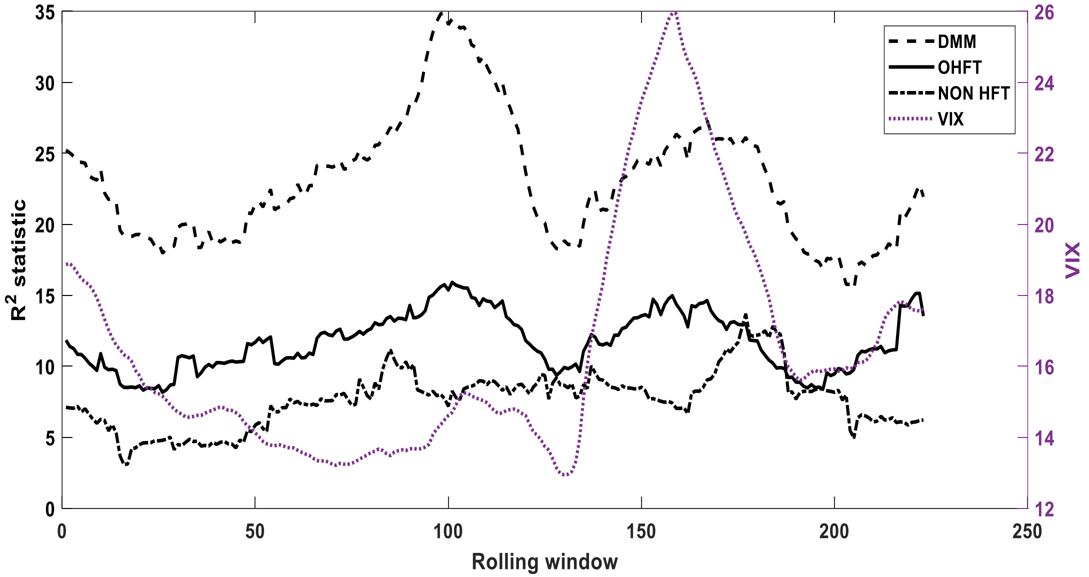
| | 1st eigenvalue ($\lambda_1$) | Explained variance | Average $R^2$ statistic |
|---|---|---|---|
| **CT (q=1)** | | | |
| DMM | 9.96 | 30.18% | 26.06%* °° |
| OHFT | 5.58 | 16.90% | 12.19%* |
| NON HFT | 3.76 | 11.38% | 6.61% |
| **CT (q=200)** | | | |
| DMM | 11.98 | 36.30% | 32.52%* °° |
| OHFT | 6.16 | 18.66% | 14.02%* |
| NON HFT | 5.23 | 15.84% | 11.16% |
| **IM** | | | |
| DMM | 8.95 | 27.43% | 23.30%* °° |
| OHFT | 5.39 | 16.50% | 11.79%* |
| NON HFT | 2.90 | 10.00% | 5.97% |

- * denote rejection of the null hypothesis that between HFT (DMM or OHFT) and NON HFT, the across-stocks average difference in the adjusted $R^2_{i,j}$ is equal to zero.
- °° denote rejection of the null hypothesis that between DMM and OHFT, the across-stocks average difference in the adjusted $R^2_{i,j}$ is equal to zero.

# Co-movement: Volatile vs Normal days




Co-movement: cost of trade CT (q=1)




Co-movement: IM

- Let w be a 25 day rolling window through the sample year (KM, 2008)
- Obtain $C_{w,i} = R^2_{w,i}$ for each security and for each rolling window (Equations (1) and (2))
- Employ the CBOE VIX as an instrument for market-wide volatility: $VIX_w$ averaged across days

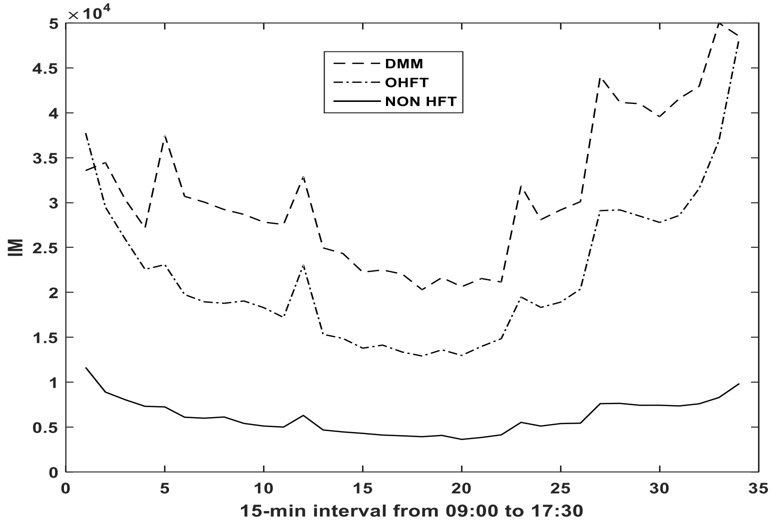
# Co-movement: Volatile vs Normal days

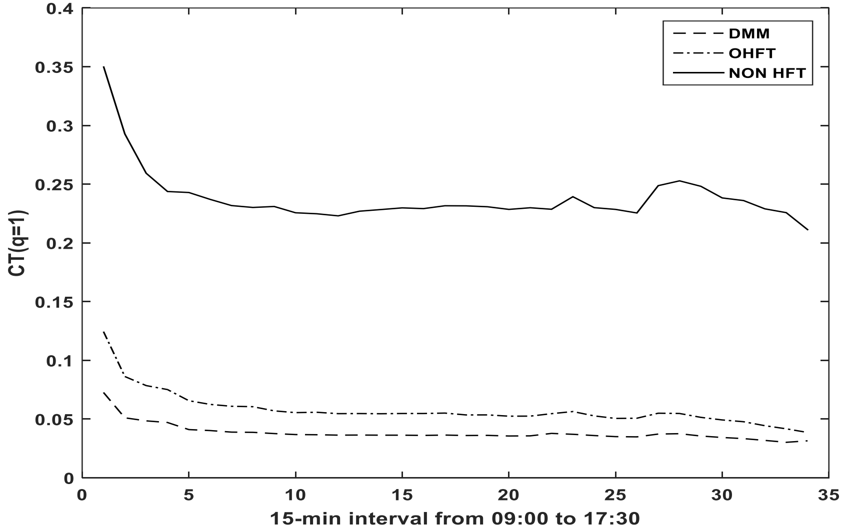
| | CT (q=1) | | CT (q=200) | | IM | |
|---|---|---|---|---|---|---|
| Equation (3) | *b* | t-statistic | *b* | t-statistic | *b* | t-statistic |
| DMM | 0.469 | 2.888* | 0.361 | 2.525* | 0.766 | 3.019* |
| OHFT | 0.830 | 2.539* | 0.915 | 2.876* | 0.802 | 2.336* |
| NON HFT | 1.096 | 2.023* | 0.850 | 1.766** | 0.244 | 0.260 |
| Equation (4) | | | | | | |
| DMM | 0.159 | 4.597* | 0.152 | 4.438* | 0.745 | 3.925* |
| OHFT | 0.160 | 2.530* | 0.107 | 1.836** | 0.535 | 3.108* |
| NON HFT | 0.305 | 3.275* | 0.272 | 2.873* | 0.460 | 1.683** |

* 95% ** 90%, N-W errors

- Regress changes of co-movement on changes of VIX: $\Delta \mathrm{C}_{\mathrm{w,i}} = \mathrm{a_i} + \mathrm{b_i}\Delta VIX_w + e_w$ (3)
- Regress changes of liquidity on changes of VIX: $\Delta \mathrm{L}_{\mathrm{w,i}} = \mathrm{a_i} + \mathrm{b_i}\Delta VIX_w + e_w$ (4)

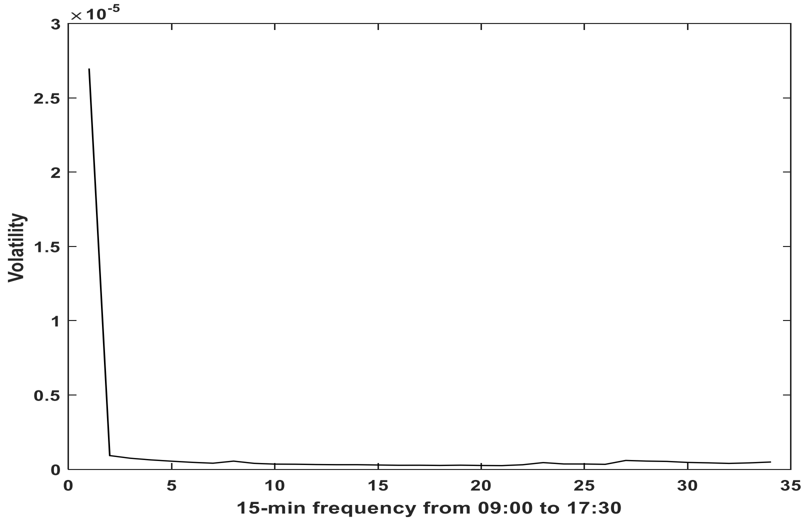
# Co-movement: time of the day

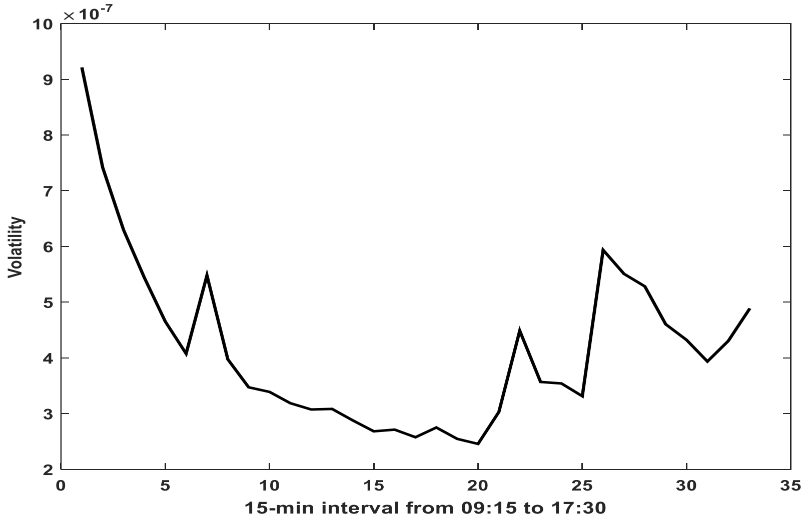



- ❑ Intraday pattern of 15-min liquidity:

Left: IMM
Right: CT

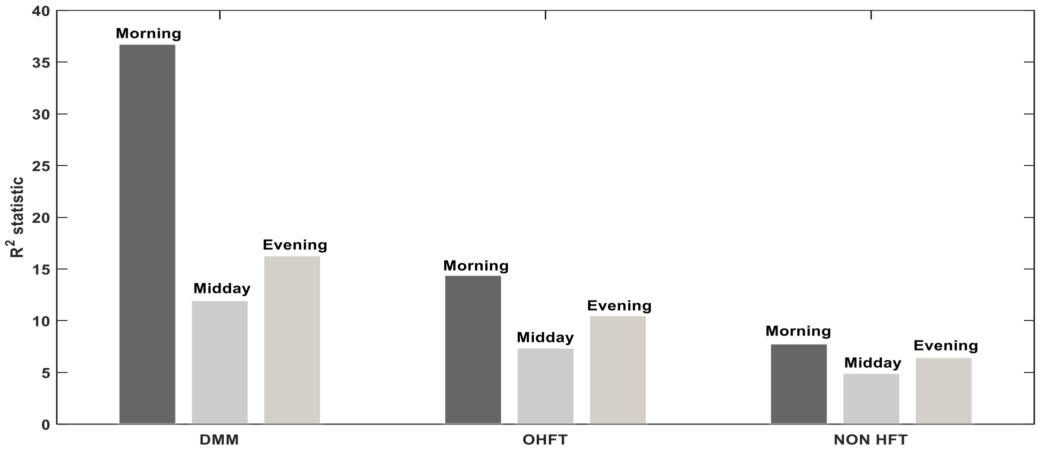


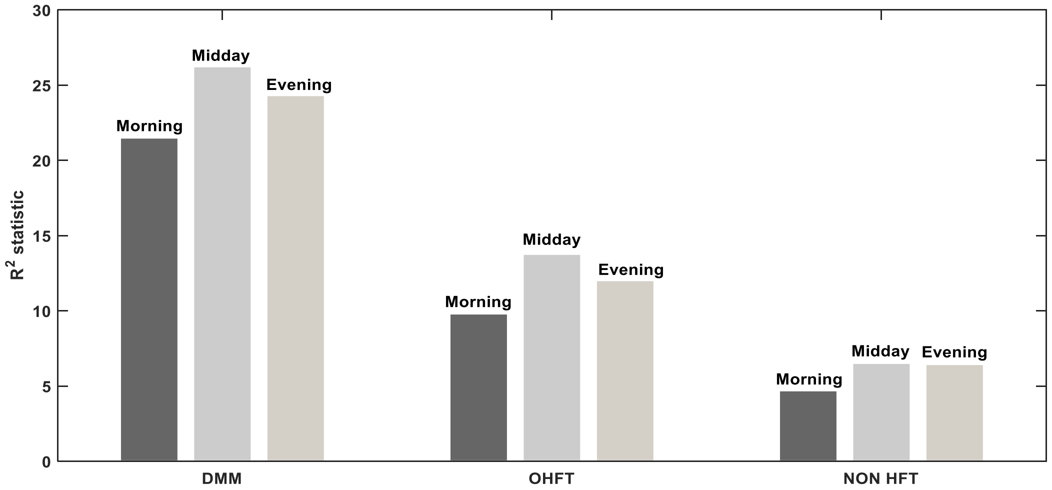

- ❑ Intraday pattern of 15-min volatility:

Left: Including first 15 minutes
Right: Excluding first 15 minutes

# Co-movement: time of the day




Co-movement: cost of trade (q=1)




Co-movement: Immediacy or passive volume

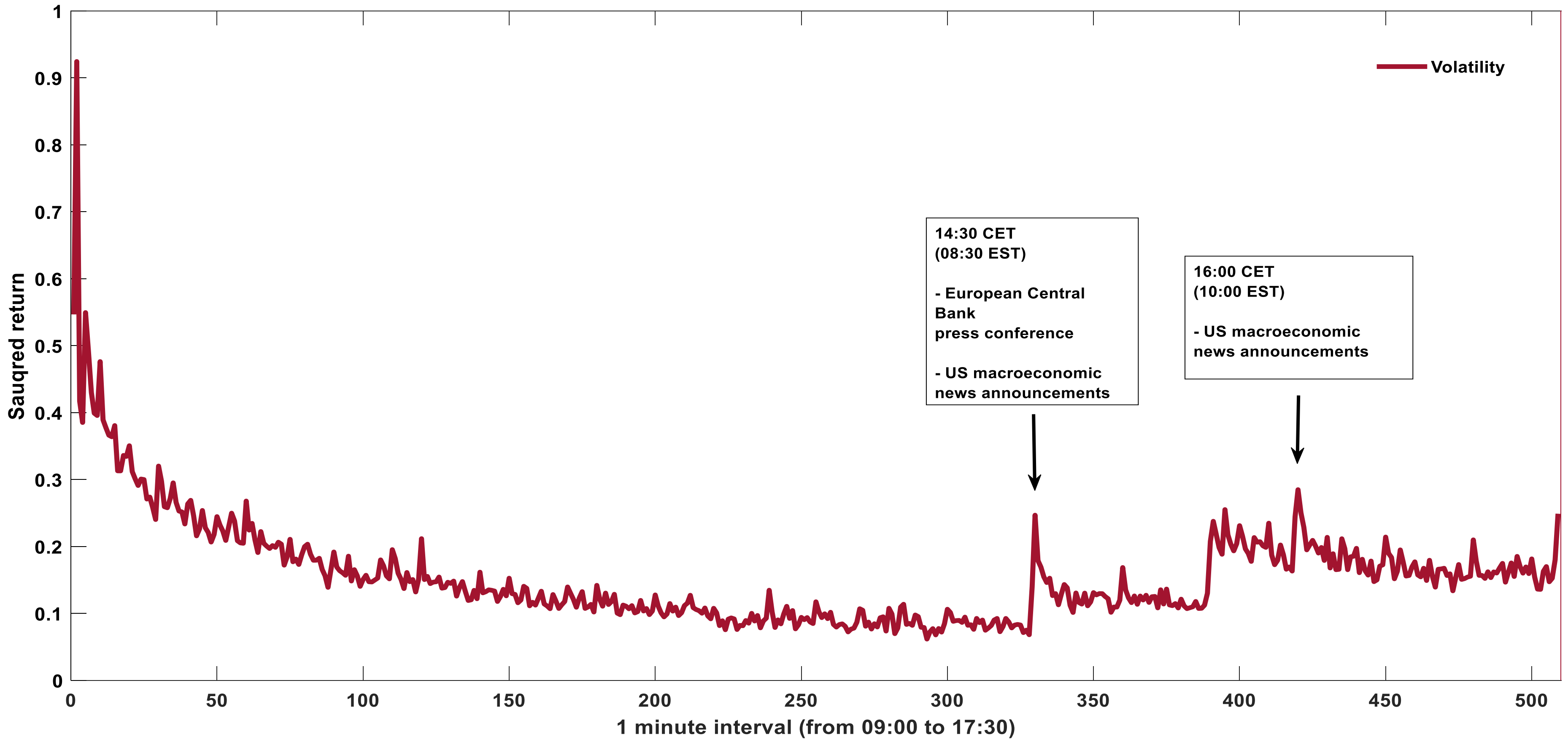
- Split the sample into three intraday periods:

Morning: 09:00 - 12:00
Midday: 12:00 - 14:45
Evening: 14:45 - 17:30

- Estimate equation (2) for each sub-sample.
- Simple t-test: $\bar{R}^2_{Morning} = \bar{R}^2_{Midday}, \bar{R}^2_{Midday} = \bar{R}^2_{Evening}$
- Results hold after controlling for single security intraday volatility and market return
- Co-movement in the cost-of-trade: U shape
- Co-movement in immediacy: inverse U shape
- HFT DMMs and OHFTs are the highest sources of liquidity market risk

# Volatility around macro-news

- 1 minute volatility (squared returns)



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# Liquidity around macro-news

| *1-min Interval* | *14:25-14:26* | *14:26-14:27* | *14:27-14:28* | *14:28-14:29* | ***14:29-14:30*** | ***14:30-14:31*** | *14:31-14:32* | *14:32-14:33* | *14:33-14:34* | *14:34-14:35* | *14:35-14:36* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **CT (q=1)** | | | | | | |
| Dummy | $\bar{D}^j_{-4}$ | $\bar{D}^j_{-3}$ | $\bar{D}^j_{-2}$ | $\bar{D}^j_{-1}$ | $\bar{D}^j_{0}$ | $\bar{D}^j_{+1}$ | $\bar{D}^j_{+2}$ | $\bar{D}^j_{+3}$ | $\bar{D}^j_{+4}$ | $\bar{D}^j_{+5}$ | $\bar{D}^j_{+6}$ |
| $j =$ DMM | 0.02 | -0.01 | 0.01 | 0.04 | **0.49**$^{*}$ | **-0.28**$^{*}$ | **-0.12**$^{**}$ | -0.06 | 0.03 | 0.00 | -0.01 |
| $j =$ OHFT | 0.01 | -0.02 | 0.00 | 0.02 | **0.25**$^{*}$ | -0.08 | -0.08 | 0.00 | 0.01 | 0.00 | -0.01 |
| $j =$ NON HFT | 0.00 | -0.01 | -0.01 | 0.08 | 0.03 | 0.08 | -0.03 | -0.05 | 0.00 | -0.01 | 0.00 |
| | | | | | **IM** | | | | | | |
| Dummy | $\bar{D}^j_{-4}$ | $\bar{D}^j_{-3}$ | $\bar{D}^j_{-2}$ | $\bar{D}^j_{-1}$ | $\bar{D}^j_{0}$ | $\bar{D}^j_{+1}$ | $\bar{D}^j_{+2}$ | $\bar{D}^j_{+3}$ | $\bar{D}^j_{+4}$ | $\bar{D}^j_{+5}$ | $\bar{D}^j_{+6}$ |
| $j =$ DMM | **-0.18**$^{*}$ | **-0.23**$^{*}$ | **-0.22**$^{*}$ | **-0.27**$^{*}$ | **-0.29**$^{*}$ | -0.08 | -0.08 | **0.22**$^{*}$ | **0.15**$^{*}$ | 0.04 | 0.05 |
| $j =$ OHFT | **-0.16**$^{*}$ | **-0.20**$^{*}$ | **-0.19**$^{*}$ | **-0.21**$^{*}$ | **-0.16**$^{*}$ | 0.08 | -0.06 | 0.01 | -0.06 | -0.08 | -0.06 |
| $j =$ NON HFT | -0.08 | -0.09 | -0.08 | -0.09 | -0.06 | 0.01 | -0.02 | -0.01 | -0.01 | -0.02 | -0.01 |

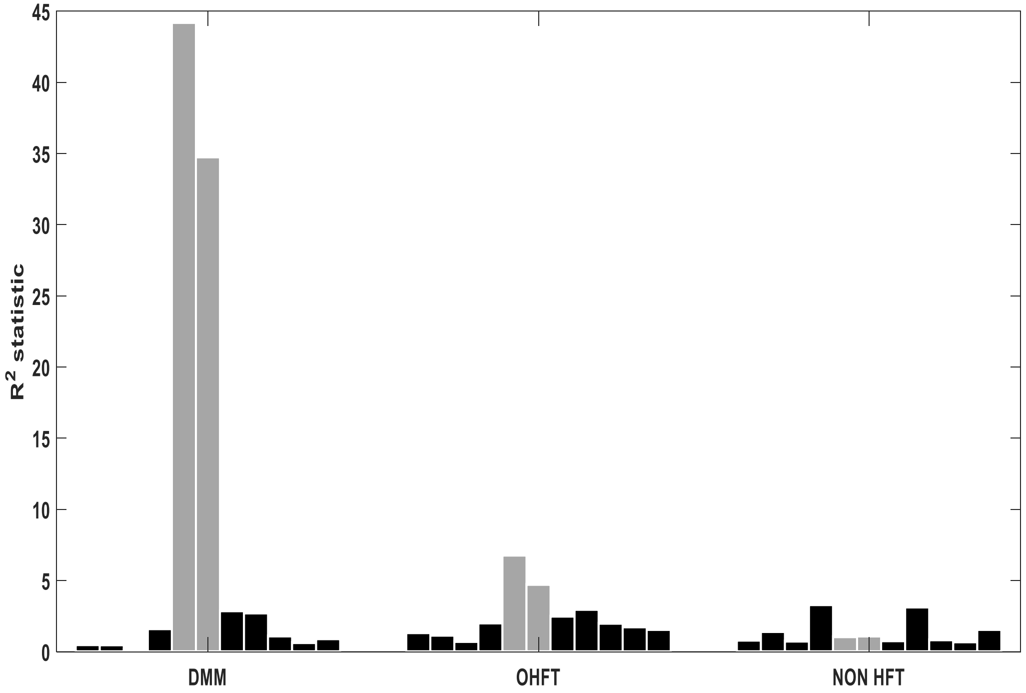
- $\omega^j_{i,t} = b^0_{i,j} + b^1_{i,j}\omega^j_{M,t} + b^2_{i,j}\omega^j_{M,t-1} + b^3_{i,j}\omega^j_{M,t+1} + Dummies + \epsilon_{i,j,t}$
- $D_\tau$, with $\tau = \{-4, -3, \ldots, +5, +6\}$,

from 14:25 CET to 14:36 CET (that is, around 14:30 CET)

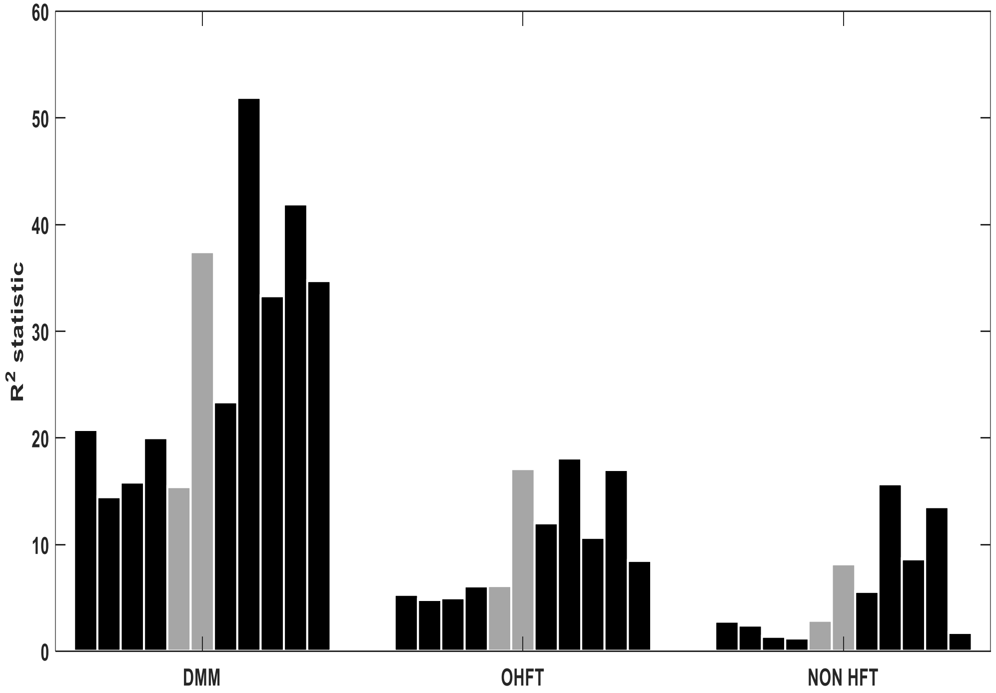
- Single asterisks denote significance at the 95% level.
- Double asterisks denote significance at the 90% level.

# Co-movement around macro-news

Cost of trade: CT (q=1)




Immediacy: IM




- We fix the 1-minute intraday interval and repeat our methodology over the trading days

# Conclusions

- We investigate the role of high-frequency traders (HFTs) in liquidity commonality for the CAC 40 Index constituents listed on the Euronext Paris Exchange.

- The literature on microstructure theory has focused more on the impact of HFT on firm-specific liquidity, whereas liquidity co-movement has received less attention thus far.

- Our analysis shows that HFTs exhibit higher co-variation in their liquidity supply compared to NON HFTs, in line with existing evidence that the use of sophisticated algorithms enhances the diffusion of information across securities.

- Nonetheless, we demonstrate that a certain fraction of the excessive co-variation in HFT liquidity is likely to be related to the activities of DMMs (e.g., through common inventory handling strategies). Our results indicate, also, that order size and market timing are important sources of liquidity co-movement.

- Implications:
  a) “slice and dice” techniques are more suitable for handling large orders.
  b) securities that are heavily traded by HFTs are likely to be associated with elevated levels of systematic risk, particularly when market stress is higher.
  c) Policy makers in the Paris market should consider new regulations that will enhance the liquidity provision process when price uncertainty is higher