# The effect of Google search volume on retail investor trades

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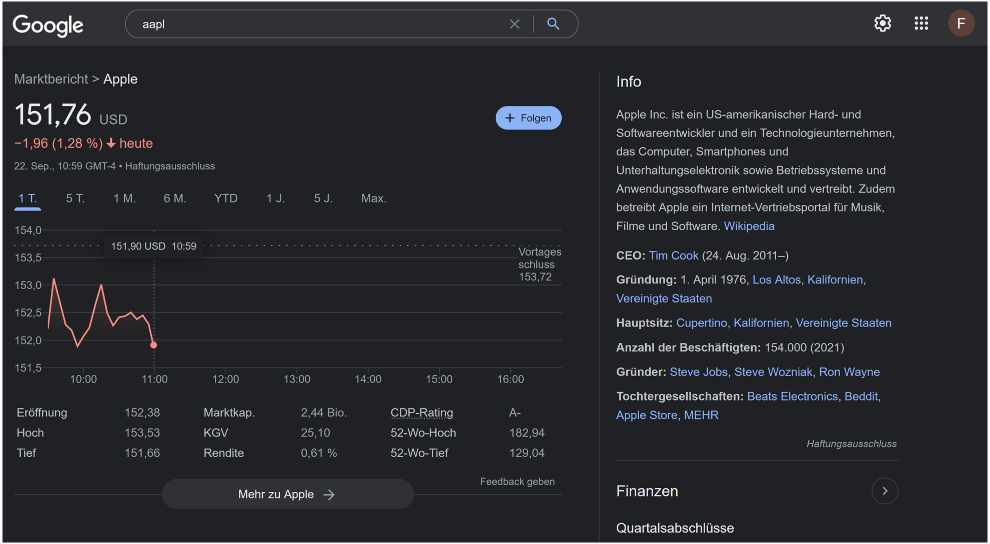
# Which type of investor knows this screen?

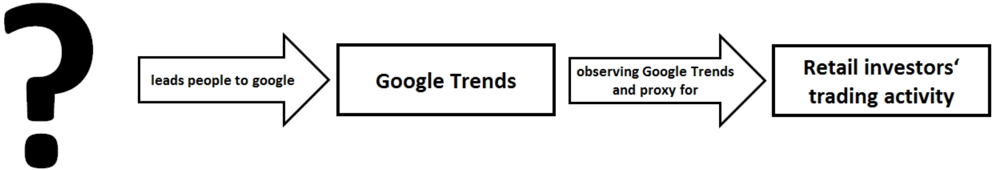
# … and which investor knows this screen?



# Do retail investors use Google and trade thereafter?

Starting with Da, Engelberg, et al. (2011) and their cautious statement that Google's Search Volume Index (SVI) "likely measures the attention of retail investors":

- assumed that retail investors use Google to inform themselves about stocks
- consensus that Google Trends captures the attention of retail investors



# SVI implicitly assumed as retail investor attention

- **Stock returns**
  Joseph et al. (2011); Bae and W. Wang (2012); Takeda and Wakao (2014); Zhang and Y. Wang (2015); Mbanga et al. (2019); Hao and Xiong (2021); Yuan et al. (2022); Da, Hua, et al. (2022)
- **Fixed Income, Commodities, Futures and REIT returns**
  Vozlyublennaia (2014); Chen et al. (2016); Yung and Nafar (2017)
- **Volatility**
  Hamid and Heiden (2015); Irresberger et al. (2015); Dimpfl and Jank (2016)

# SVI implicitly assumed as retail investor attention – cont'd

- **Liquidity**
  Da, Engelberg, et al. (2011); Bank et al. (2011); Ding and Hou (2015); Cheng et al. (2021)
- **IPO valuation**
  Colaco et al. (2017); Kao et al. (2022)
- **Herding**
  Hsieh et al. (2020); Gavish et al. (2021); Wanidwaranan and Padungsaksawasdi (2022)

# Contribution

- Combination of SVI and orderbook data
- Observing effects of Abnormal search volume (ASVI) on retail investor trades
- **New approach:** directly observing retail investor trades, based on the trade identification algorithm by Boehmer et al. (2021)

**Finding I**

- ASVI positively related to retail investor trading activity

**Finding II**

- ASVI positively related to all other market participants trading activity as well

# S&P 500 constituents

- All 550 constituents of the S&P 500 during the years 2018 and 2019 from CRSP

- Orderbook data (NBBO and Trades) from NYSE TAQ
- Exchanges: NYSE, AMEX, NASDAQ, NYSE Arca
- Sample period of 502 trading days: 01.01.2018 until 31.12.2019

- News data from Bloomberg
- Price and return data from CRSP

- Search volume index with geographical location US from Google Trends

# Google search volume index [1]

Table: SVI – Screening procedure

| | |
|---|---|
| All Ticker | 550 |
| Excluded in Step 1<br>*Ticker is a word* | 18 |
| Excluded in Step 2<br>*No financial information supplied* | 101 |
| Excluded in Step 3<br>*No financial information demanded* | 48 |
| Excluded in Step 4<br>*At least 50% of the time SVI is available* | 85 |
| Valid Ticker | 298 |

[1] following Niessner (2015) and Kupfer and Schmidt (2021)

# Retail investor trades

We apply the trade classification algorithm by **Boehmer et al. (2021)**

- most retail trades occur off-exchange via wholesalers or internalisation
- appear as trades with exchange code "D" in TAQ data
- buyer-initiated trades by retail investors are below a round penny (sub-penny interval of [0.6, 1])
- seller-initiated trades by retail investors are above a round penny (sub-penny interval of [0, 0.4])

# Remaining trades

We apply the three most popular trade classification algorithms and match NBBO and Trade by up to one millisecond, following Holden and Jacobsen (2014)

**Lee and Ready (1991)** convention

- buyer initiated if $Price_i > Midpoint_i$
- seller initiated if $Price_i < Midpoint_i$

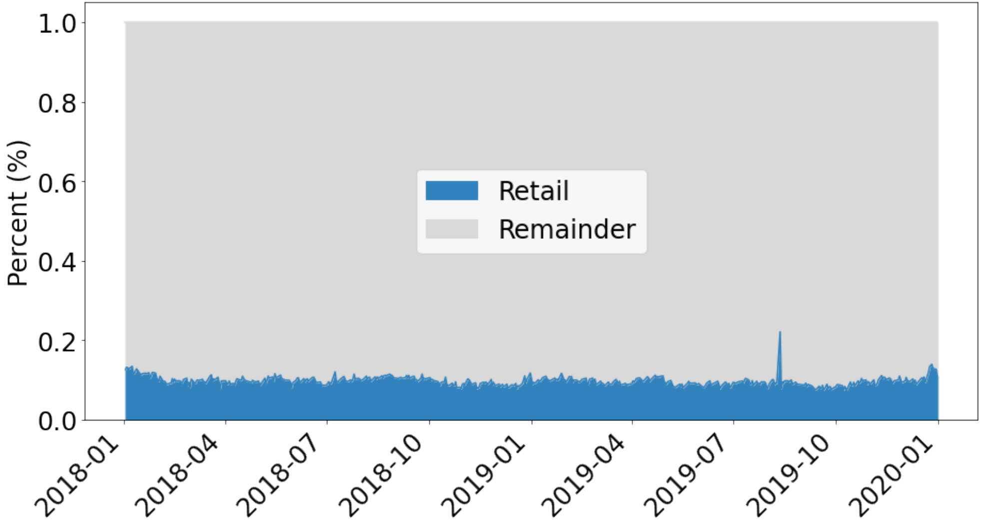
**Ellis et al. (2000)** convention

- buyer initiated if $Price_i = Ask_i$
- seller initiated if $Price_i = Bid_i$

**Chakrabarty et al. (2007)** convention

- buyer initiated if $Price_i \in [0.3 * Bid_i + 0.7 * Ask_i, Ask_i]$
- seller initiated if $Price_i \in [Bid_i, 0.7 * Bid_i + 0.3 * Ask_i]$

# Total dollar volume of buyer initiated trades



# ASVI, abnormal buys and sells and other controls

**Abnormal search volume index**

$ASVI_{i,t} = ln(SVI_{i,t}) - ln(Mean(SVI_{i,t-1}, ..., SVI_{i,t-20}))$

**Abnormal number of buyer (seller) initiated trades**

$ANBuys_{i,t} = ln(NBuys_{i,t}) - ln(Mean(NBuys_{i,t-1}, ..., NBuys_{i,t-20}))$

Other investor attention proxies as used in Ben-Rephael et al. (2017)

- Abnormal news: $ANews_{i,t} = ln(1 + News_{i,t}) - ln(Mean(News_{i,t-1}, ..., News_{i,t-20}))$
- Abnormal trading volume: $AVol_{i,t} = ln(Vol_{i,t}) - ln(Mean(Vol_{i,t-1}, ..., Vol_{i,t-20}))$
- $Ret_{i,t}$, $Abs(Ret_{i,t})$, $Ret_{i,t-1:t-5}$ and $Ret_{i,t-6:t-53}$ – Actual and past returns
- $\sigma_{i,t-1:t-5}$ – Past volatility
- $Spread_{i,t}$ – Percentage effective spread
- $IntraVola_{i,t}$ – Intraday volatility
- $HLtoH_{i,t}$ – Relative price range

# Abnormal number of buyer initiated trades

$$AN_{i,t}^{Buys,c} = \alpha + \beta * ASVI_{i,t} + \sum_{k=1}^{K} \theta_k * X_{i,t}^{k} + \tau_t + \mu_i + \epsilon_{i,t} \quad (1)$$

| | (1) Retail | (2) LR | (3) EMO | (4) CLNV |
|---|---|---|---|---|
| *ASVI* | 0.043*** | 0.018*** | 0.018*** | 0.018*** |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| *ANews* | 0.055*** | 0.039*** | 0.039*** | 0.039*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $Avol_{t-1}$ | 0.301*** | 0.343*** | 0.336*** | 0.338*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| *Other Controls* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| $R^2$ | 0.456 | 0.604 | 0.630 | 0.615 |
| *Observations* | 121,267 | 121,267 | 121,267 | 121,267 |

Complete regression output: ANBuys

# Abnormal number of seller initiated trades

$$AN^{Sells,c}_{i,t} = \alpha + \beta * ASVI_{i,t} + \sum_{k=1}^{K} \theta_k * X^k_{i,t} + \tau_t + \mu_i + \epsilon_{i,t} \quad (2)$$

| | (1) Retail | (2) LR | (3) EMO | (4) CLNV |
|---|---|---|---|---|
| *ASVI* | 0.042*** | 0.019*** | 0.019*** | 0.019*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *ANews* | 0.048*** | 0.043*** | 0.043*** | 0.043*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $Avol_{t-1}$ | 0.271*** | 0.349*** | 0.364*** | 0.356*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| *Other Controls* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| $R^2$ | 0.513 | 0.619 | 0.603 | 0.612 |
| *Observations* | 121,267 | 121,267 | 121,267 | 121,267 |

Complete regression output: ANSells

# Beware when using Google!

The ‘implicit’ assumption that Google Trends captures the attention of retail investors seems to be true, but there is some by-catch.

Our results indicate that:

- Google Trends captures an unobserved attention generating event
- those events lead retail investors to trade
- **but** those events also lead all other market participants to trade

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# *ANBuys* – Complete regression output

| | (1) Retail | (2) LR | (3) EMO | (4) CLNV |
|---|---|---|---|---|
| *Constant* | -0.451*** | -0.199*** | -0.186*** | -0.194*** |
| | (0.018) | (0.015) | (0.014) | (0.014) |
| *ASVI* | 0.043*** | 0.018*** | 0.018*** | 0.018*** |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| *ANews* | 0.055*** | 0.039*** | 0.039*** | 0.039*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $Avol_{t-1}$ | 0.301*** | 0.343*** | 0.336*** | 0.338*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| *HLtoH* | 3.542*** | 3.970*** | 4.128*** | 4.037*** |
| | (0.139) | (0.114) | (0.108) | (0.111) |
| *Spread* | -23.818*** | -87.652*** | -82.300*** | -87.018*** |
| | (3.521) | (2.873) | (2.738) | (2.804) |
| *IntraVola* | 236.885*** | 292.304*** | 296.848*** | 293.664*** |
| | (5.315) | (4.337) | (4.134) | (4.233) |
| $Ret_t$ | -0.740*** | 0.479*** | 0.242*** | 0.390*** |
| | (0.052) | (0.042) | (0.040) | (0.041) |
| $Abs(Ret_t)$ | 5.904*** | 4.051*** | 3.786*** | 3.920*** |
| | (0.088) | (0.071) | (0.068) | (0.070) |
| $Ret_{t-1:t-5}$ | -0.402*** | -0.171*** | -0.159*** | -0.165*** |
| | (0.024) | (0.019) | (0.018) | (0.019) |
| $Ret_{t-6:t-53}$ | 0.196*** | 0.070*** | 0.095*** | 0.080*** |
| | (0.008) | (0.007) | (0.007) | (0.007) |
| $\sigma_{t-1:t-5}$ | -2.942*** | -3.104*** | -3.133*** | -3.102*** |
| | (0.098) | (0.080) | (0.077) | (0.078) |
| *52HighDum* | 0.095*** | 0.047*** | 0.040*** | 0.043*** |
| | (0.004) | (0.003) | (0.003) | (0.003) |
| *52LowDum* | 0.097*** | 0.032*** | 0.026*** | 0.030*** |
| | (0.006) | (0.005) | (0.005) | (0.005) |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| $R^2$ | 0.456 | 0.604 | 0.630 | 0.615 |
| *Observations* | 121,267 | 121,267 | 121,267 | 121,267 |

# *ANSells* – Complete regression output

| | (1) Retail | (2) LR | (3) EMO | (4) CLNV |
|---|---|---|---|---|
| *Constant* | -0.444*** | -0.194*** | -0.209*** | -0.199*** |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| *ASVI* | 0.042*** | 0.019*** | 0.019*** | 0.019*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *ANews* | 0.048*** | 0.043*** | 0.043*** | 0.043*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $Avol_{t-1}$ | 0.271*** | 0.349*** | 0.364*** | 0.356*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| *HLtoH* | 2.790*** | 4.510*** | 4.358*** | 4.473*** |
| | (0.118) | (0.116) | (0.120) | (0.119) |
| *Spread* | -24.294*** | -77.291*** | -83.699*** | -76.839*** |
| | (2.983) | (2.943) | (3.042) | (3.002) |
| *IntraVola* | 236.119*** | 313.824*** | 309.825*** | 313.384*** |
| | (4.503) | (4.443) | (4.593) | (4.532) |
| $Ret_t$ | -0.414*** | -0.087** | 0.076* | -0.072* |
| | (0.044) | (0.043) | (0.045) | (0.044) |
| $Abs(Ret_t)$ | 6.208*** | 3.601*** | 3.920*** | 3.719*** |
| | (0.074) | (0.073) | (0.076) | (0.075) |
| $Ret_{t-1:t-5}$ | -0.315*** | -0.297*** | -0.353*** | -0.325*** |
| | (0.020) | (0.020) | (0.020) | (0.020) |
| $Ret_{t-6:t-53}$ | 0.203*** | 0.155*** | 0.132*** | 0.150*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $\sigma_{t-1:t-5}$ | -2.251*** | -3.505*** | -3.542*** | -3.549*** |
| | (0.083) | (0.082) | (0.085) | (0.084) |
| *52HighDum* | 0.078*** | 0.026*** | 0.032*** | 0.028*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| *52LowDum* | 0.094*** | 0.024*** | 0.030*** | 0.025*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| $R^2$ | 0.513 | 0.619 | 0.603 | 0.612 |
| *Observations* | 121,267 | 121,267 | 121,267 | 121,267 |

# $SOI$ – Complete regression output

| | (1) Retail | (2) LR | (3) EMO | (4) CLNV |
|---|---|---|---|---|
| *Constant* | -1.337*** | -1.140*** | 3.960*** | 2.785*** |
| | (0.055) | (0.107) | (0.089) | (0.082) |
| *ASVI* | 0.196*** | -0.704*** | 0.240*** | -0.270*** |
| | (0.039) | (0.074) | (0.062) | (0.057) |
| *ANews* | -0.151*** | -0.345*** | -0.329*** | -0.365*** |
| | (0.022) | (0.043) | (0.036) | (0.033) |
| *Savol* | 0.269*** | -0.682*** | -0.046* | -0.291*** |
| | (0.010) | (0.031) | (0.026) | (0.024) |
| *HLtoH* | 35.682*** | -108.148*** | 14.638*** | -54.417*** |
| | (3.328) | (6.377) | (5.330) | (4.894) |
| *Spread* | 726.958*** | -3,113.035*** | 2,887.498*** | -1,992.808*** |
| | (73.839) | (142.253) | (118.903) | (109.169) |
| *IntraVola* | 827.030*** | 5,223.041*** | -5,845.260*** | -1,099.409*** |
| | (118.001) | (227.592) | (190.235) | (174.661) |
| $Ret_t$ | -7.564*** | 31.578*** | -0.599 | 20.398*** |
| | (1.240) | (2.368) | (1.979) | (1.817) |
| $Abs(Ret_t)$ | -35.725*** | 15.395*** | 2.108 | 8.318*** |
| | (2.190) | (4.104) | (3.430) | (3.149) |
| $Ret_{t-1:t-5}$ | 0.359 | 10.911*** | 6.166*** | 8.417*** |
| | (0.562) | (1.078) | (0.901) | (0.827) |
| $Ret_{t-6:t-53}$ | -2.265*** | -10.141*** | -1.837*** | -6.845*** |
| | (0.195) | (0.375) | (0.313) | (0.287) |
| $\sigma_{t-1:t-5}$ | -8.423*** | -24.847*** | -21.418*** | -33.778*** |
| | (2.212) | (4.246) | (3.549) | (3.259) |
| *52HighDum* | 0.245*** | 0.086 | 0.756*** | 0.545*** |
| | (0.093) | (0.178) | (0.149) | (0.137) |
| *52LowDum* | -0.086 | 2.951*** | -1.599*** | 0.924*** |
| | (0.152) | (0.291) | (0.243) | (0.223) |
| *Time FE* | Yes | Yes | Yes | Yes |
| $R^2$ | 0.018 | 0.026 | 0.030 | 0.033 |
| *Observations* | 115,298 | 115,298 | 115,298 | 115,298 |