Outline

1. Market overview
2. Flash crash
3. Intertrade durations as carriers of information
4. Long-memory dynamics: Hurst coefficient and rescaled range analysis
5. Conclusions
1. Market Overview

- Trades convey information
- Market-makers (“specialists”) observe market activity
  - Learn information content
  - Adjust quoted prices
- Prices reflect the expectation of security terminal value
  - Net Present Value (NPV) of future cash flows
  - Conditional on all public information, including prior trades
- Price adjustment is gradual
  - Short-run effect
  - Long-run effect
    - Hasbrouck (1991)
1. Market Overview

- Information variables affecting prices:
  - News
    - Macroeconomic releases
    - Corporate earnings
    - Political news
    - ...
  - Trade prices
  - Trade sizes
  - Best bid/best offer quotes
  - Best bid/best offer sizes
  - Shape of the order book
  - Duration between trades
  - Duration between quote “arrival”
1. Markets have three types of “agents”

- Market-makers/Specialists
  - Possess only public information
  - Infer most information from prices
- Informed traders are “in the know”
  - Closely following news
  - Superior research
  - Not necessarily insider information
- Uninformed traders trade regardless of current price levels
  - Retail gamblers
  - Hedgers
    - Commodity farmers, manufacturers using raw ingredients may hedge using futures
    - International companies may hedge cross-border flows using foreign exchange
- Consumption needs
  - Individuals and corporations may need to liquidate investments
    - In order to finance their day-to-day spending
    - To reallocate investments according to portfolio strategies
    - To reflect personal risk sensitivity – close off positions that are too risky
1. Recent Developments

- Technology impact on markets:
  - Investors automate their trading (Hendershott and Riordan, 2009)
  - Most markets are electronic limit order books (Jain, 2005)
  - Use of trading algorithms is on the rise;
    - Automate trading decisions
    - Submit orders
    - Manage orders post-submission
  - Buy-side and sell-side engage in high-frequency trading
  - Sell-side must understand buy-side trading strategies to avoid being picked off
1. Algorithms

- Two types:
  - High-frequency trading: arbitrage of intraday market inefficiencies
    - Includes market-making
  - Order-splitting facilitation of execution
    - To minimize market impact, associated costs

- All algorithms initiate an increasing proportion of trades
  - In January 2008 on Deutsche Borse (according to Henderschott and Riordan, 2010):
    - Algorithms initiated 52% of trading volume.
      - 68% of all trades of less than 500 shares
      - 23% of all trades of 10,000 or more
    - Algorithms are observed to cluster their trades close to one another.
    - Algos are more sensitive to trades initiated by human traders than human traders are to algos.
    - Algos are less likely to initiate trades following high market volume.
    - Algos' behavior does not change following high volatility conditions.
    - Human trading generates most noise in foreign exchange trading (Chaboud et al., 2009)
1. Algorithmic Trades Carry Information

- Algo-initiated market orders carry 20% larger permanent price impact than do human trades
  - Human trades are more likely to be random relative to realized prices that follow
  - Algo trades impound 40% more information than do human trades
  - Yet, algorithms are better at disguising their trading intentions.
  - Algos are more likely to initiate trades when liquidity is high (higher depth and narrower bid-ask spreads)
- Algo-initiated limit orders are at the best price more often than human limit orders
  - In normal market conditions, algos supplied 50% of Deutsche Borse DAX liquidity in January 2008
  - When liquidity is lower, algorithms supplied more liquidity than humans
    - Humans withdrew liquidity more often than algos
- Algos consume liquidity when cheap and supply liquidity when it is expensive, smoothing liquidity over time.
1. Execution algorithms lower costs

- Different algorithms deliver different execution costs (Domowitz and Yegerman, 2005).
- Algorithm aggressiveness impacts execution costs (Engle, Russell, and Ferstenberg, 2007).
- Can be used by traders to accumulate or liquidate a large position by breaking up orders into pieces
- Execution algos select
  - Timing of order parcels
  - Size of each parcel
  - Level of aggressiveness
    - Ranging from market orders (most aggressive)
    - To stub quotes (most passive)
- To avoid being “picked off” algos cancel many limit orders when they fail to execute
  - The orders are often resubmitted almost immediately at a price closer to market
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2. Flash Crash – May 6, 2010

- Second-largest point swing of the Dow Jones Industrial Average in history (1,010.14 points)
- Biggest one-day point decline (998.5 points)
- Caused by:
  - Waddell & Reed deploying a Percent of Volume (POV) algorithm to execute a sale of 75,000 E-mini contracts on the S&P 500
    - According to findings of the joint SEC and CFTC commissions, next came “two liquidity crises – one at the broad index level in the E-mini, the other with respect to individual stocks.”
    - Not clear if the POV was programmed correctly (accounting for the trader’s own trades in the previous period)
    - Not a ‘fat finger,’ but a ‘fat brain’ error
  - Technical delays of price reporting by NYSE and ARCA also contributed to the crash (confirmed by NYSE)
  - Nanex blamed “quote stuffing” for slowing down systems
2. The joint SEC and CFTC report

- “May 6 started as an unusually turbulent day for the markets”
- “broadly negative market sentiment was already affecting an increase in the price volatility of some individual securities”
- “backdrop of unusually high volatility and thinning liquidity”
- “a large fundamental trader (a mutual fund complex) initiated a sell program to sell a total of 75,000 E-Mini S&P 500 contracts (valued at approximately $4.1 billion) as a hedge to an existing equity position.”
- Percent Of Volume (POV) algorithm:” target an execution rate set to 9% of the trading volume calculated over the previous minute, but without regard to price or time.”
2. Flash Crash Risk Factors

• An imbalance between trades (dominance of buys vs sells)
• High volume and low liquidity conditions
  • The ‘flash crash’ of 2010 was preceded by an imbalance of trades and liquidity: liquidity was low
  • According to Easley, Lopez de Prada, and O’Hara (2010)
• Concentration of liquidity provision in the hands of few highly specialized firms
• Withdrawal of retail investors
• Low capitalization of liquidity providers, resulting in high sensitivity to intraday losses
2. HFT Market Makers

- Turn over their inventory 5 or more times a day (Easley, Lopez de Prada, O’Hara, 2010)
- Balanced supply and demand markets are perfect for HFT market-making
- Unbalanced volumes may cause losses for market makers (HFT and non-HFT) due to adverse selection
  - Informed traders have better information than market makers
  - As a result, informed traders extract wealth from market makers (Easley and O’Hara, 1992)
  - Market makers gain most revenue from uninformed market participants
  - When the proportion of informed traders is high, the market-makers lose money, may withdraw from markets

High volume imbalance causes crashes

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2. HFT Market Makers in Flash Crash

• On May 6, 2010:
  • Goldman Sachs had 10 days of trading losses, including three days of over $100 million trading losses
  • Morgan Stanley reported similar losses
  • Bank of America reported similar losses
  • TD Ameritrade did not disclose losses, but reported “record number of trades.”
2. VPIN: Metric for Volume Imbalance

To measure the volume balance, use VPIN metric:

- Average sell-side less buy-side initiated trading volume divided by the average volume during the period under consideration
- In the absence of exact information of whether a trade is a buy or a sell, consider the trade a buy if it occurred at a price above the mid-quote
- Similarly, a sell-initiated trade is designated as such if it occurred at a price below the mid-quote
- \( VPIN = \frac{1}{V} \left( \frac{1}{N} \sum |V^B - V^S| \right) \)
- Periods with lots of information-based trades would typically have high volume imbalance
- Prior to ‘flash crash’:
  - VPIN was abnormally high at least one week ahead of the crash
  - VPIN rose to record levels several hours before the crash
  - VPIN preceded other indices, such as VIX, in rising ahead of the crash
2. VPIN properties in normal markets

• Derived from probability of informed trading
• Can be interpreted as volume-based probability of informed trading
  • Informed traders trade in one direction
  • Uninformed traders withdraw

• VPIN for E-minis S&P 500 futures summary statistics:
  • Fits lognormal distribution
  • Median value: around 39%
    • Interpretation: 50% of time, volume-based probability of informed trading is 39% or less
  • VPIN of 44% or above occurs only 20% of time
    • 80% of time, probability of volume-based informed trading in the S&P 500 E-mini futures is 44% or less
  • On May 6, 2010, VPIN exceeded 90%.
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3. Informed Traders

- Always trade on news (good or bad)
  - Buys on good news
  - Sells on bad news
  - The only exception: in the case of bad news, if the informed trader does not own shares, and there are short-sale constraints, the informed investor cannot trade

- To take advantage of the news, informed traders would like to:
  - Trade as quickly as possible
  - Trade as much as possible

- However, if an informed trader trades large block of data on news
  - Other traders would see the trades, infer the news direction, trade on the same information, distort demand/supply dynamics for the informed traders, lessen returns for the informed traders

Informed traders are better off trading slowly, breaking up large orders into small order parcels

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3. Trading intensity

- Time between trades
- Shorter time between trades => higher trading intensity
- Higher trading intensity:
  - Higher price impact of trades
  - Faster price adjustment to new trade-related information
  - Stronger “directionality” of trades
    - Directionality: predominance of trades of similar size and the same direction (buy or sell)
    - Detected using autocorrelation
  - High trading intensity has been shown to result from activity of informed traders
    - Alternative view: high trading intensity originates from informed and uninformed traders pooling together to trade at low costs (low costs coming from market makers possessing extra inventory and offering tight spreads, for example). This theory has been invalidated by Dufour and Engle, 2001.
  - High trading intensity deters uninformed traders
3. Trading Intensity

- When trading intensity is high:
  - Inter-trade durations are short
  - Quote revisions are large following each trade
  - Strong positive autocorrelation of trade characteristics:
    - A buy after a short inter-trade duration is likely followed by another buy (Dufour and Engle, 2000)
    - An algo order is likely followed by another algo order (Henderschott and Riordan, 2010)
    - A small order is likely to be followed by a small order, large by large (Biais, Hillion and Spatt, 1995; Parlour, 1998; Henderschott and Riordan, 2010)
  - Liquidity providers raise probability of a news event
    - Some liquidity providers stop trading
    - Some liquidity providers widen spreads
    - Quotes are adjusted faster
  - Trades carry higher informational content
    - Trades are likely placed by “informed traders”
  - Trades incur greater market impact
    - Markets are less liquid as a result
3. Models for Inter-trade Duration

• **Time deformation**
  • Transformations relate economic time to calendar time (Ghysels and Jasiak, 1998)
  • Trade time may also be measured by volume increments (Easley, Lopez de Prada, O’Hara, 2011).
    • Volume time: the fraction of the average day’s volume that has executed up to a clock time $t$ (Almgren et al, 2005)
    • In analysis, map each clock time $t_0, \ldots, t_n$ to a corresponding volume time $\tau_0, \ldots, \tau_n$

• **Autoregressive conditional duration (Engle, 1997)**
  • Dependent point process
  • Convenient for modeling clustering and overdispersion
  • Distributions:
    • Weibull distribution
      - $g(\tilde{T}_t) = \frac{\theta}{\phi_t} T^{\theta-1} \exp \left[ - \left( \frac{\tilde{T}_t}{\phi_t} \right)^\theta \right]$ for $\theta > 0, \phi_t > 0$
    • Exponential distribution is a special case of Weibull ($\theta = 1$)
    • When $\theta < 1$: overdispersion with extreme values (very short or very long durations)

• **Survival models**
• **Poisson models**
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4. Key question

- Can inter-trade durations predict crashes?
- Was the pattern of inter-trade durations normal during the flash crash?
4. Long-Memory Dynamics

- Used to detect long-memory patterns
- Is data purely random?
  - Are fractals random? Yes and no
  - Some pattern-like evolution of markets may exist
  - If so, we can detect market abnormalities relative to their steady state

- Statistics:
  - On average, how many minutes of data comprise 10,000 ticks of Level I ticks of S&P 500 ETF (NYSE:SPY)?
  - Does the data evolve at random?
4. Inter-trade Dynamics

- On average, 10,000 ticks of Level I data of SPY from Reuters Datascope comprise just ONE minute of data
  - 1 second ~ 1,700 ticks of Level I data: quotes and trades, not cancellations
- Yet, on average, the price of SPY moves only every two seconds
- The price moves when trades carry and impound information
- The more information is out there, the higher the number of trades occurring, the faster the price moves up or down
- Inter-trade time durations can pinpoint period of information
4. Identification of abnormal activity -- Methodology

- Data is considered self-similar when its statistical properties remain similar in time: the latest observations are statistically comparable with previous ones.
- Data can be tested for self-similarity in a variety of ways:
  - Rescaled range (R/S) analysis assesses self-similarity via an approximation to the so-called Hurst exponent.
  - The Hurst exponent measures randomness of data, and was first noted by Mandelbrot and Wallis (1969) in fractal design.
  - Hurst exponent, $H$, of 0.5 corresponds to random data, while $H > 0.5$ identifies trending data, and $H < 0.5$ pinpoints mean-reverting data.
  - A proper Hurst exponent ranges from 0 to 1.
4. R/S methodology

The R/S approximation to Hurst exponent utilizes a simplified computational framework that proceeds as follows (see Qian and Rasheed (2004)):

- Step 1: Calculate the mean of the entire time series: \( m = \frac{1}{n} \sum_{i=1}^{n} X_i \)
- Step 2: Calculate de-meaned series \( Y: Y_t = X_t - m, t = 1, 2, \ldots, n \)
- Step 3: Calculate “cumulative deviate” series \( Z: Z_t = \sum_{i=1}^{t} Y_i, t = 1, 2, \ldots, n \)
- Step 4: Calculate range \( R: R_t = \max(Z_1, Z_2, \ldots, Z_t) - \min(Z_1, Z_2, \ldots, Z_t) \), \( t = 1, 2, \ldots, n \)
- Step 5: Calculate a running mean for each observation \( t: u_t = \frac{1}{t} \sum_{i=1}^{t} X_i, t = 1, 2, \ldots, n \)
- Step 6: Calculate standard deviation series \( S: S_t = \sqrt{\frac{1}{t} \sum_{i=1}^{t} (X_i - u_t)^2}, t = 1, 2, \ldots, n \)
- Step 7: Calculate rescaled range series \((R/S): (R/S)_t = R_t/S_t\) for all \( t \)’s that are whole powers of two: \( t = 2, 4, 8, 16, 32, \ldots, 1024, 2048, 4096, \ldots \) as long as \( t < n \)
- Step 8: Plot \( \log_2(R/S)_t \) vs. \( \log_2 t \) for \( t = 2, 4, 8, 16, 32, \ldots, 1024, 2048, 4096, \ldots \) and estimate the slope of the resulting line. The slope is the R/S approximation to the Hurst exponent.
4. May 6, 2010: A cluster of spikes in R/S of inter-trade durations in SPY
4. R/S Intertrade duration

- SPY data
- Median: 1.035
- 75%: 1.377
4. R/S Intertrade Durations vs. Cumulative Returns
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5. Conclusions

- The methodology can be used to screen markets real-time for potentially onsets of flash crashes
- The methodology would generate selected false positives, but enough upside with long-enough warning to offset the effects of false signals
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