Tail Risk & Cross-Asset Infrastructure

Global Derivatives, Trading & Risk Management,
Amsterdam, May 2014

Vladimir Chorniy, Head of Risk Modelling Strategy,
Group Risk Management, BNP Paribas
Andrei Greenberg, Quantitative Analyst,
Green Burgundy Consulting Ltd. & BNP Paribas

Agenda

- Capturing counterparty risk in the “new world”
  - CCPs, regulators, banks may have different requirements
- Making the most of available information
  - Market-implied and historical data; structural approach
- In focus: credit and equity
- Modelling dependence
  - Correlation or cointegration
  - Common drivers (volatility, asset returns,…)
- Suggestions and preliminary conclusions

Counterparty risk today

- The way we look at counterparty risk is changing
  - Increased role of clearing and margining (EMIR, Dodd-Frank)
  - Central Counterparties (CCPs)
- Tails become more important, but specific requirements result in zooming in on different areas
  - Still need “classical” counterparty risk calculations: expectation for regulatory capital and CVA, and 90^{th} or 99^{th} percentile exposures
  - With more trades collateralised and cleared, banks focus on higher percentiles over typical slippage / no-control periods for residual risk
  - Long-term stability of the financial system would require extreme events over long horizons to be assessed
  - Cross-asset dependence can become crucial in many of these cases
- Pricing and tail risk
  - Stress scenarios for pricing model validation
  - Can more accurate modelling of tails help pricing models?

CCP and Margining

- CCP
  - Client – clearing is segment specific, but client termination is across all segment (and un-cleared trades)
  - CCP – rulebook and legal entity specific (e.g., LCH SA vs. LCH Ltd)
  - Cross-asset netting – may be; portfolio effect – definitely
  - Extreme events are expected to be propagating through majority of markets

- Margining (EMIR)
  - Margins (both VM & IM) must be exchanged between counterparties when they are both either Financial Counterparties (FC) or Non-Financial Counterparties above the clearing threshold (NFC+) according to EMIR definitions.
  - Transactions between counterparties where one of them is neither FC nor NFC+ are exempted
  - Legacy – pre-EMIR, but also pre-EBA RTS implementation

- Need to cover existing risk scope and address new

Counterparty risk: what needs to be measured and why

Percentile/Horizon	Short (10d)	Medium	Long (2y+)
Lower (Expectation; 90 - 99%)	Collateralised legacy; NFC-; IM calculation / verification – CCPs/FC, NFC+	Legacy trades and NFC- (“classical”); IM stability– CCPs/FC, NFC+; CCP	Legacy trades and NFC- (“classical”)
Higher (above 99%)	Risk above IM covered level CCP/FC, NFC+	Same	Systems stability - stress tests; Regulators; All positions

Risk factors and dependence: what to model and how (I)

- Short-term co-movement: returns
  - Returns are best for describing/predicting underlying moves over short horizons
  - Correlated diffusions or common jumps to model joint behaviour
- Long-term predictions: levels
  - Trends matter much more for long horizons: diffusive moves average out (also $O(\sqrt{\Delta t}) \ll O(\Delta t)$), effect of jumps is short-lived
  - Classical example: long-term mean of an Ornstein-Uhlenbeck process
  - Levels can be used to enforce “pathwise” dependence (e.g., in scenarios with low share prices, spreads should be high)

- Cross-asset test case: Equity-Credit
  - Relevant for equity financing, repo, SLAB
  - Some well-known fundamental relationships (jump-to-ruin, low share prices – wide spreads, etc.)
  - Structural link

Risk factors and dependence: what to model and how (II)

- Modelling quantities
  - Equity returns, share price levels
  - CDS spreads preferable to hazard rates in risk context due to observability
    - Hazard rates generate “price-able” scenarios
  - Equity volatility
  - Asset returns

- Dependence
  - Correlation (and/or common jumps) of stochastic drivers for returns
  - Cointegration, or mean-reverting “spread” between levels
  - Regime shift: time- or state-dependent correlation (e.g., higher for extreme returns than in the middle of the distribution)
  - Common drivers: if correctly incorporated, leads to better models
    - Fundamental causality: changes in the same external quantity driving changes in equity and credit
    - Mathematical stability: if a common driver exists, modelling it + relationships will produce a more robust model

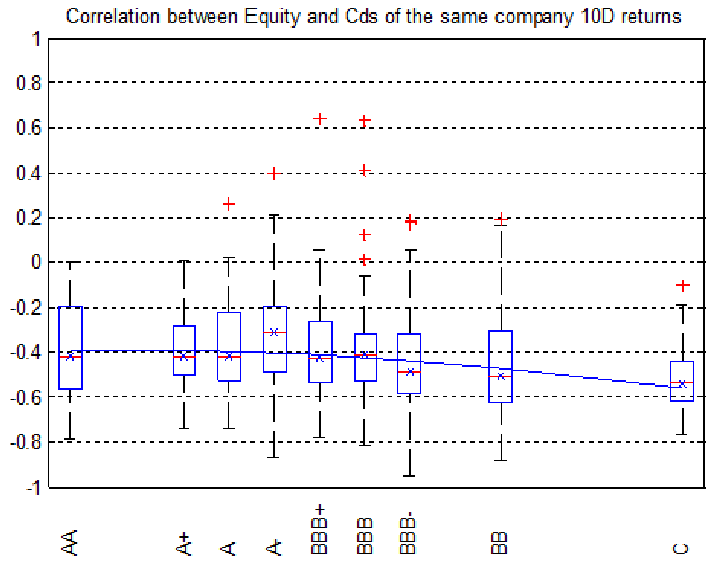
Market information

Type	Historical	Market-implied
Equity	Equity prices and returns, volatility of returns, jumps in returns	Volatility (ATM, OTM/smile) [Equity]
Credit	CDS spreads, returns and jumps; ratings	CDS spreads
Asset returns	☑	☑

- Risk models operate in the "real-world measure", so historical data are generally preferred for calibration
- However market-implied information has the advantage of forward view
  - Instantaneous CDS spreads contain information about default probabilities and can be used to predict sudden moves in equity
  - Implied volatility represents market view of future volatility of returns
- Asset returns: strictly speaking, not market data, but can be useful
  - Potential common driver for equity and credit (via structural models)
  - May be used to model rating transitions

Short-term equity-spread return correlations

- Negative correlation expected market-wide: tightening of spreads is associated with increased equity returns as share prices go up
- For individual names, some dependence on credit quality may transpire
  - Poorly rated names show stronger link:



- In this talk, we are more interested in longer term dependencies
  - Horizon of interest is several months to several years
  - Short-term correlation tends to average out on large portfolios
  - Tail risk must include long-term effects

Volatility as a common driver

- Standard common driver model is Merton's asset return construction – but should we try a new flavour?
- Volatility as a risk indicator can affect market prices of equity and debt
  - Cf. even in Merton: equity is a call and debt, a put on asset value
- Campbell & Taksler (2003): booming stock market in 1990s accompanied by rising corporate bond yields – counterintuitive?
  - Optimism of equity investors not shared by bond investors
  - Volatility may be the key: more upside for shareholders, more risk for bondholders
- Share prices and volatility of returns
  - "Leverage effect": price growth is less volatile than price drops
  - Historical volatility commonly used as a predictor of future returns distribution
- Cremers et al. (2008) : implied volatility affects credit spreads
  - Both ATM and OTM/skew explain a significant part of CDS spread levels
- Carr & Wu (2009, 2011): economic similarity between CDS and deep OTM equity puts

Relationships we can measure

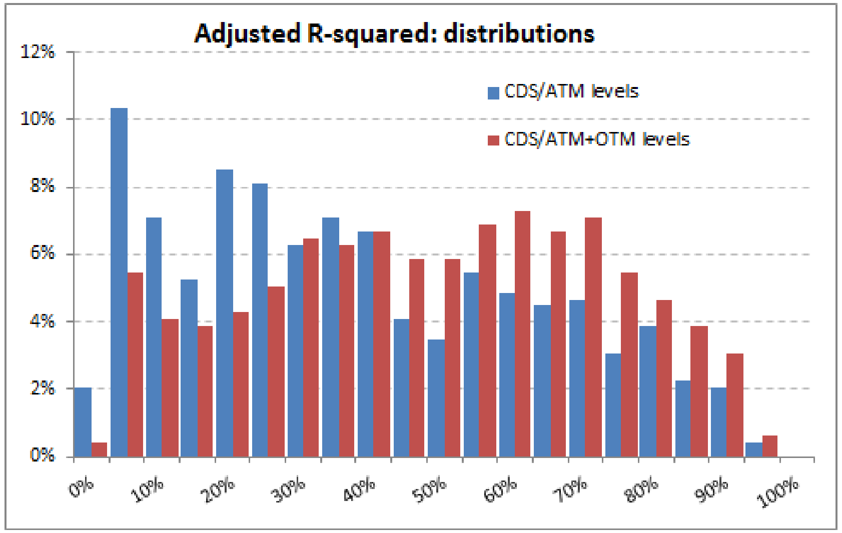
- Use linear regression at first: R^2 to indicate strength of relationship
- According to our paradigm, need to analyse various combinations
  - CDS and equity
  - Levels and returns
  - Implied and historical volatility
  - ATM volatility and skew
- Questions
  - Are CDS levels stationary?
    - Cremers et al. (2008) argue to the affirmative
  - What to use for OTM implied volatility?
    - "ATM skew" vs. "DOOM put vol"
  - If standard deviation of historical returns "corresponds" to ATM implied volatility, what is "historical skew"?
    - Stochastic volatility: correlation between equity returns and their variance (Heston)
    - Jump-diffusion: average size and intensity of jumps in equity returns (historical estimates less stable)
- "Equity levels" ?? (more on this later)

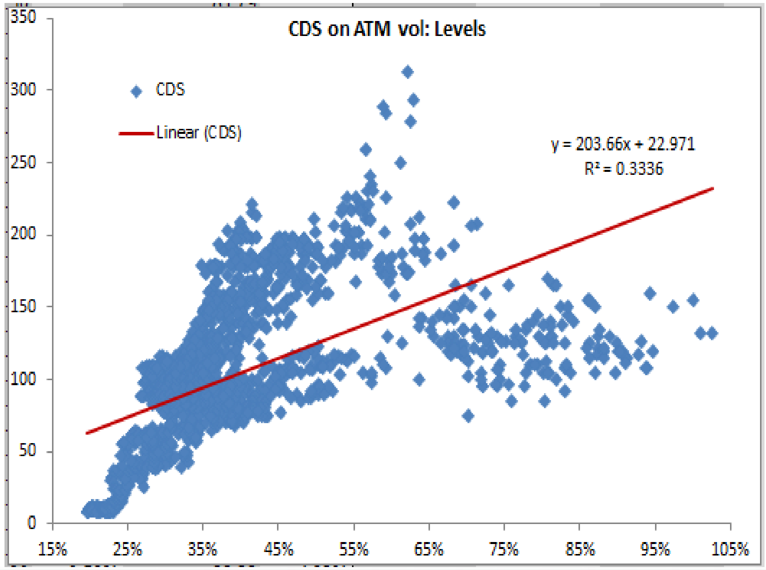
Measurement: the boring details

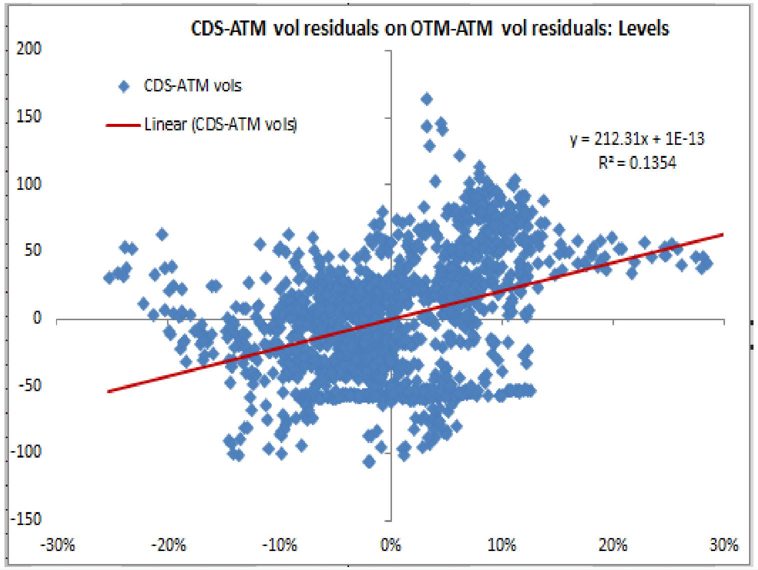
- Universe:
  - 500 names from major international equity indices with liquid CDS
  - Time series from September 2006 to August 2013
  - More liquid names subset: 160 names
- Implied volatilities:
  - 6m option implied ATM vols
  - Deep OTM put vols (extrapolated to 30% strike)
  - Skew as (ATM – OTM) / (100% - 30%) < 0 for equity
- Historical volatilities:
  - Standard deviation of 10-day returns, estimated over 6 months and annualised
  - Correlation with variance measured over 6m window
  - Time-averaged jump measures over 6m windows

CDS spread and volatility (I): levels on levels - implied

- Median R^2 is 32% for ATM vols, going up to 46% when OTM is added
- 45% and 55%, respectively, for the subset of more liquid names
- Distribution of R^2 clearly shifts to the right when skew is added
- Regressions shown for Deutsche Bank: positive slope means: high vol → wide spreads

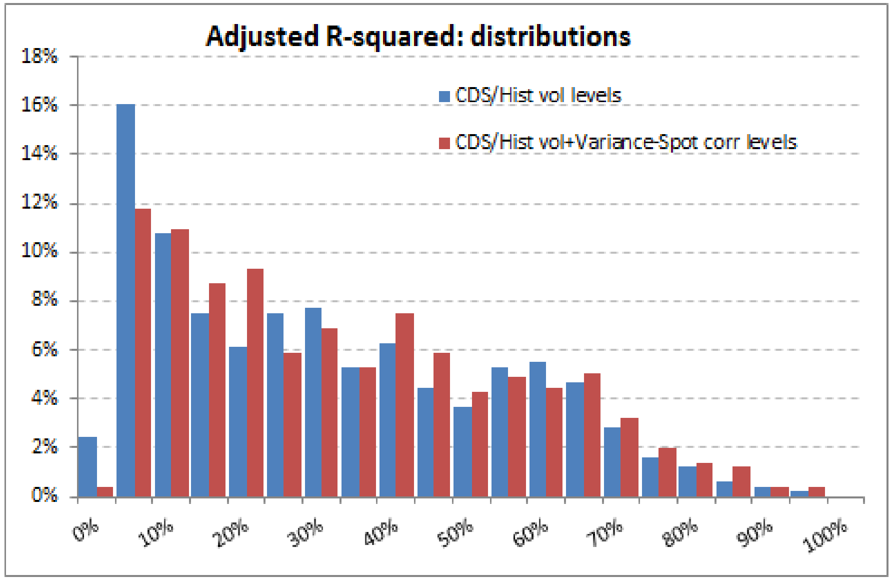


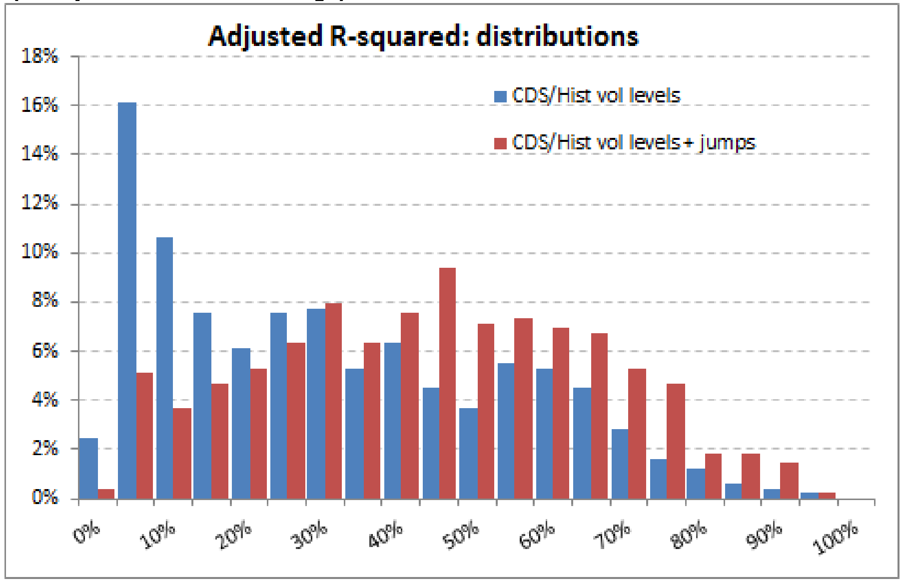




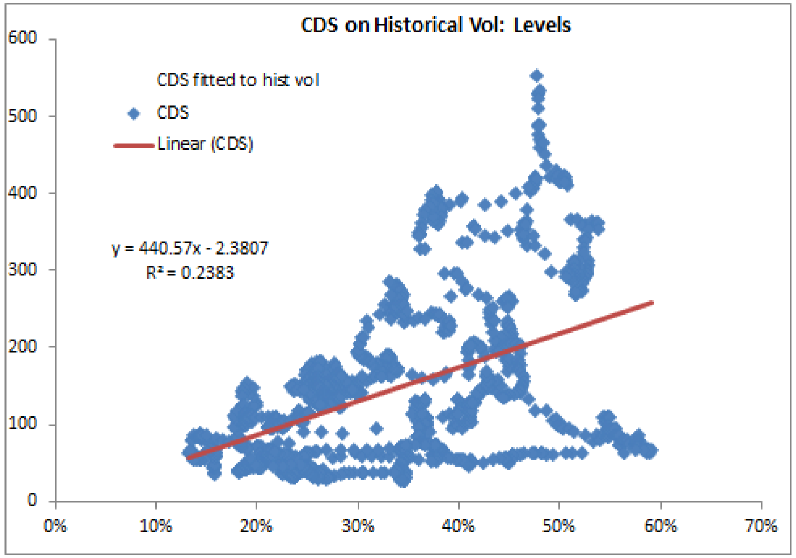
CDS spread and volatility (II): levels on levels - historical

- Weaker dependence on historical vol: median R^2 is 24% (34% for subset of more liquid names)
- Jumps explain residuals better than correlation between variance and returns
  - Median R^2 goes up to 41% (47% for liquid), vs. 27% (41% for liquid) with variance-returns correlation
  - Jump risk embedded in CDS or non-stationarity of average jump size time series?
- Related question: which language is better at describing equity dynamics, jump-diffusion or stochastic volatility? (separate study)

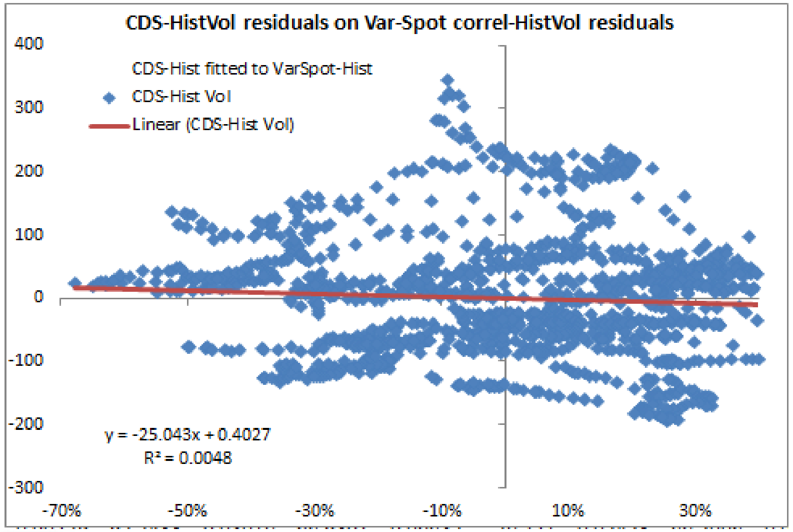


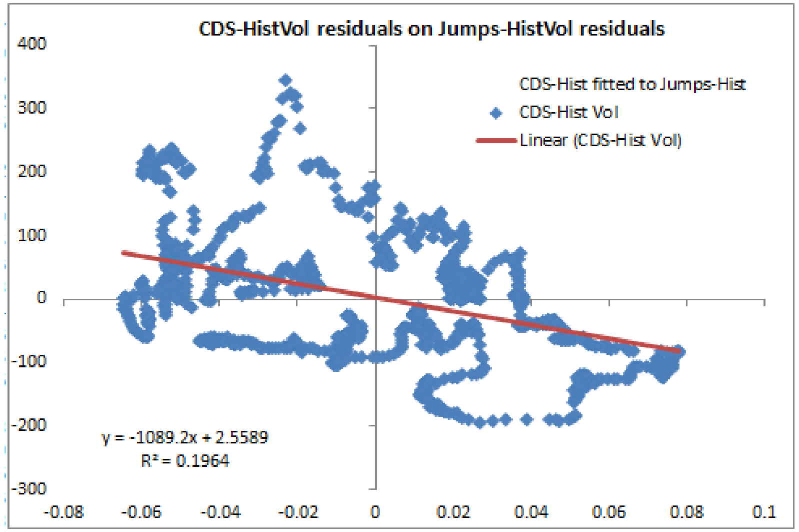


CDS spread levels on historical volatility levels: example 1

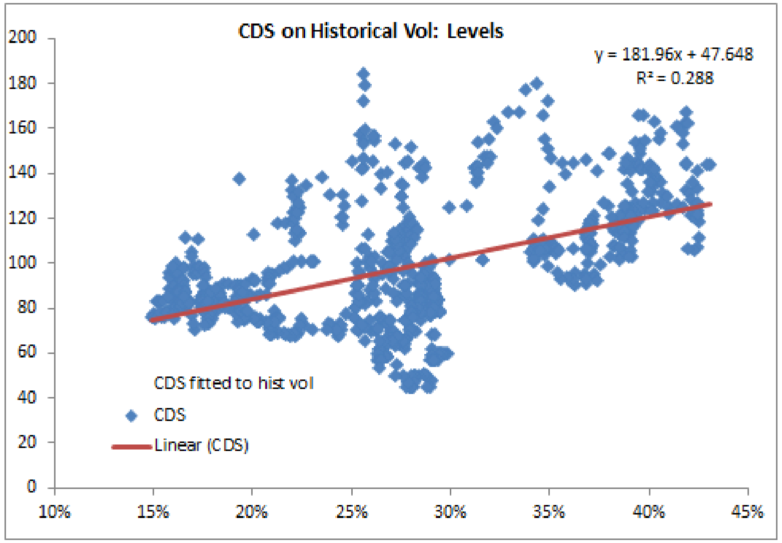


Computer Sciences Corporation: averaged jumps explain CDS residuals better than variance-spot correlation

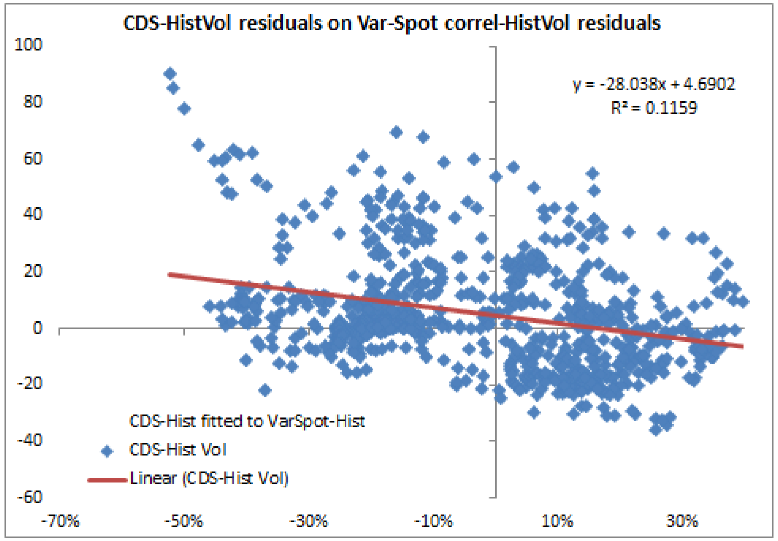


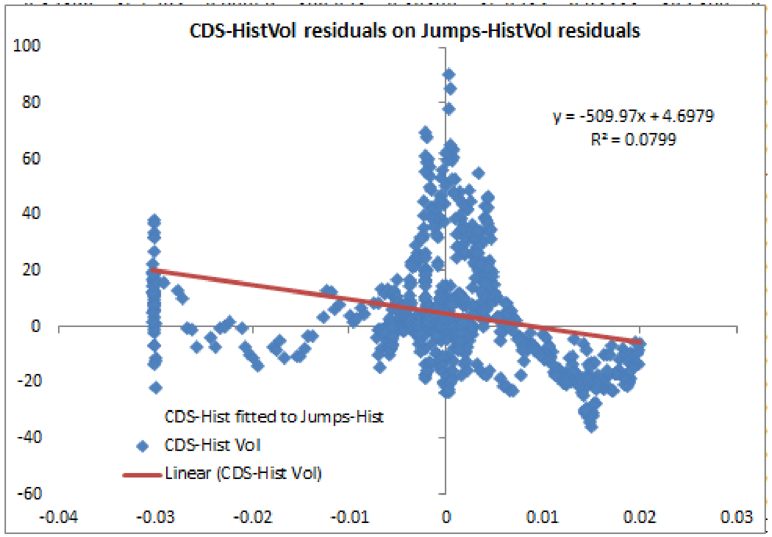


CDS spread levels on historical volatility levels: example 2



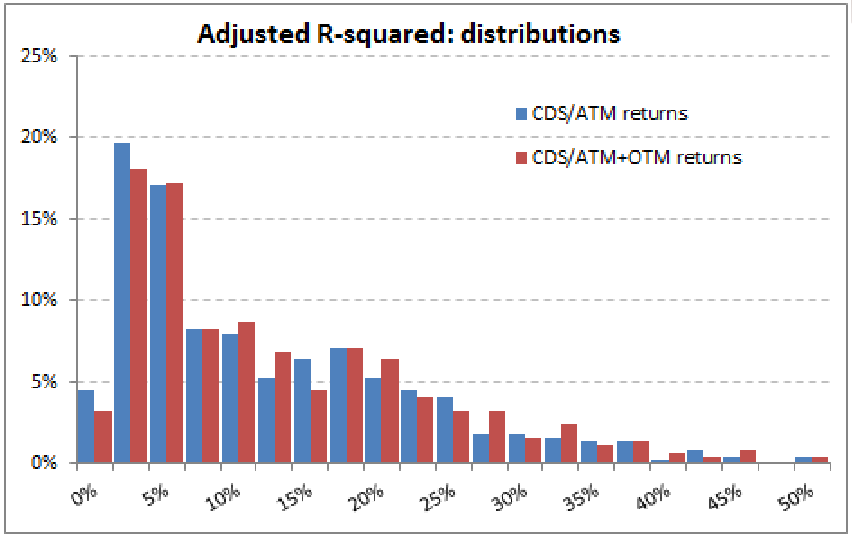
JP Morgan Chase: variance-spot correlation explains CDS residuals better than averaged jumps

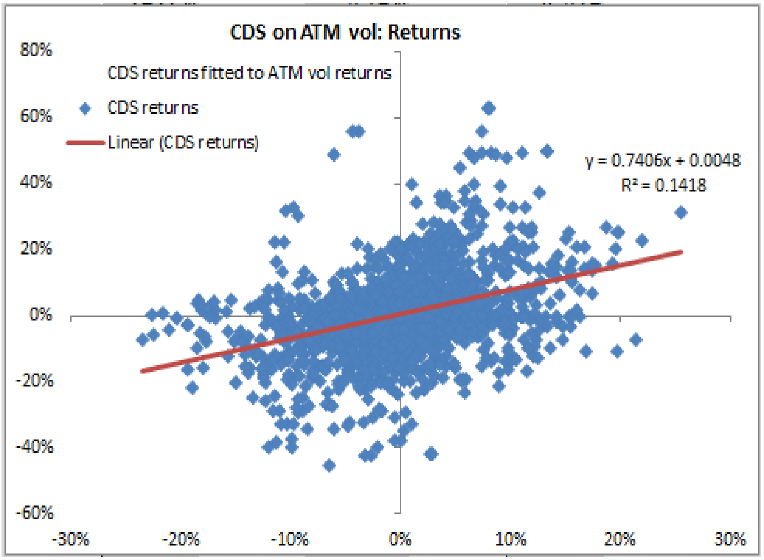


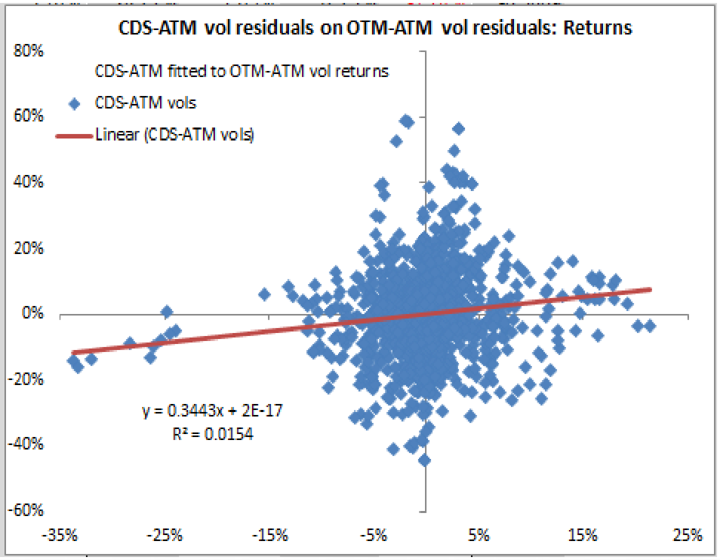


CDS spread and volatility (III): returns on returns - implied

- Very weak dependence: median R^2 is <8% for ATM vols, OTM adds nothing
- Slightly higher median R^2 (20%) for the more liquid names – still visibly smaller than levels, and no OTM effects
- Less clustering in the data than for levels
- Regressions shown below for Next plc: positive slope, just as for implied vols

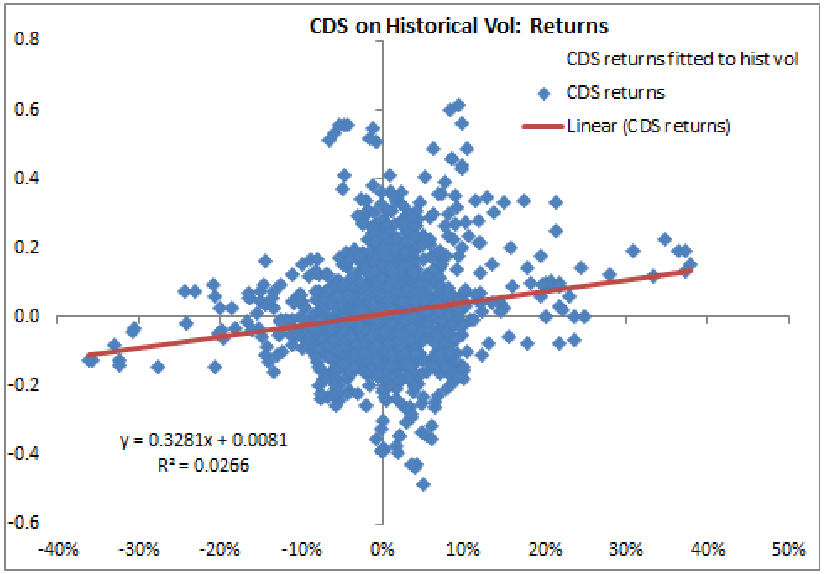


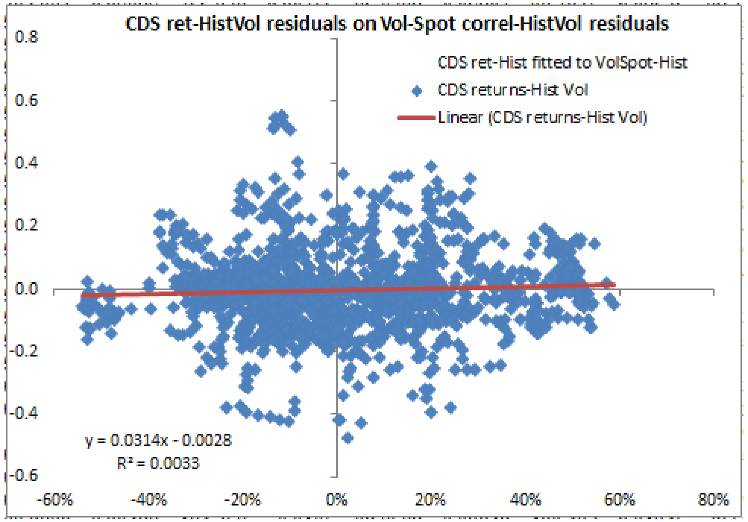


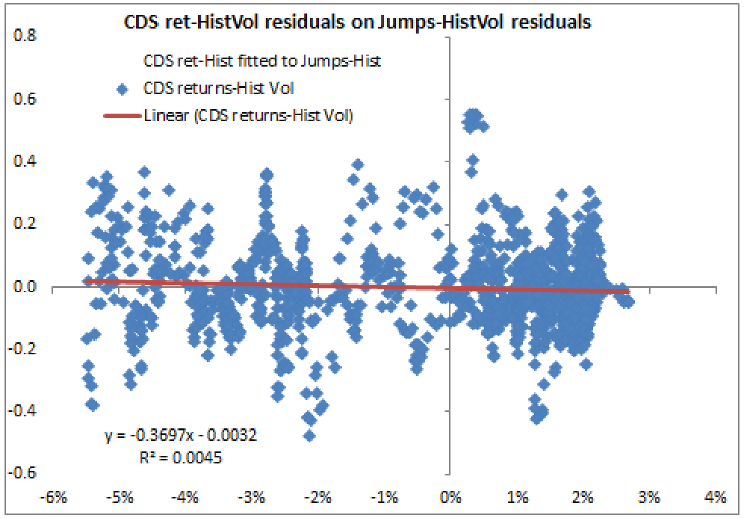


CDS spread and volatility (IV): returns on returns - historical

- Hardly any dependence at all: median R^2 is 1-3%, no matter how many historical vol returns are taken or which skew proxy is chosen
- Picture does not change for liquid names
- Regressions shown for Accor SA

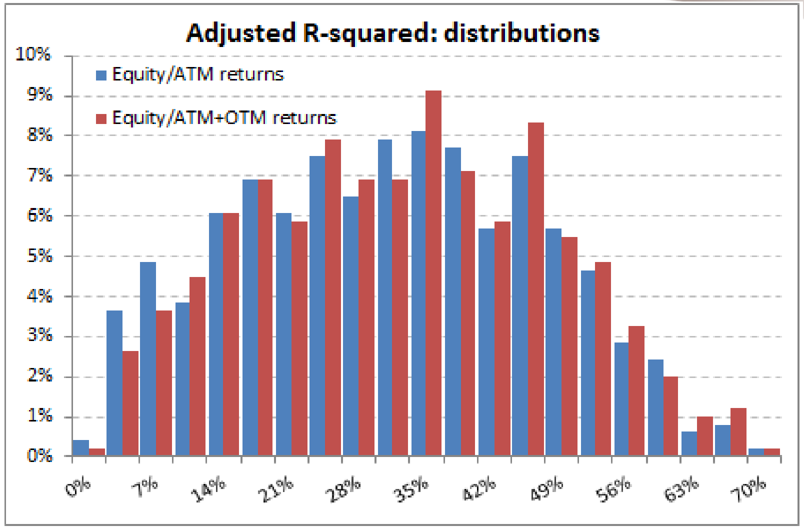


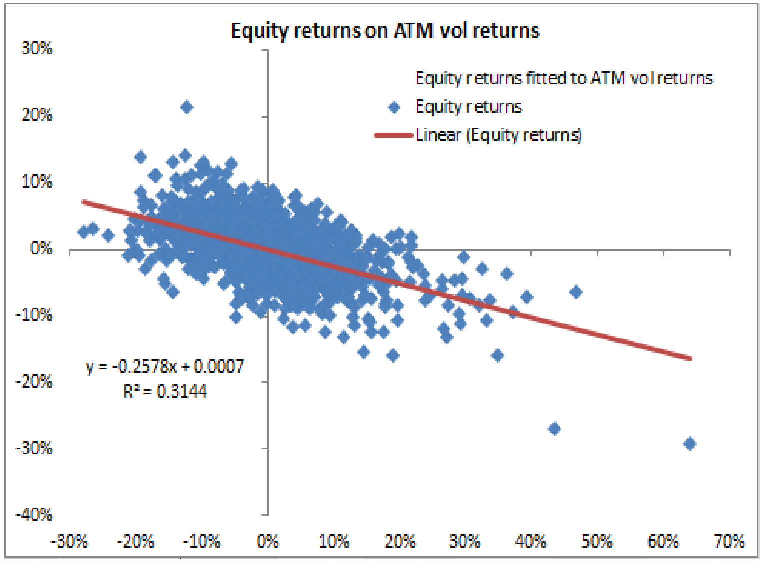


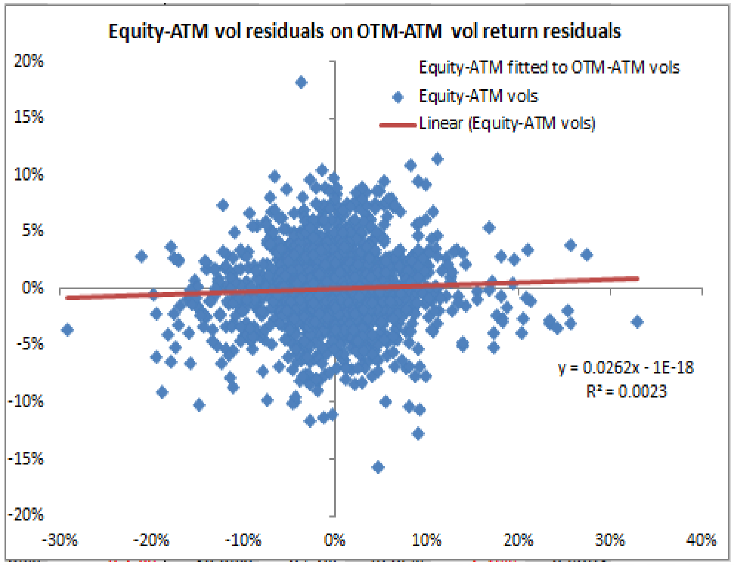


Equity and volatility (I): returns on returns - implied

- Median R^2 is 30% for ATM vol returns, OTM adds nothing
- Slightly higher median R^2 (40%) for the more liquid names, still no OTM effects
- Seems like implied volatility skew plays no role in equity returns, only ATM does
- Regressions shown below for AT&T : negative slope means: high vol → low equity returns

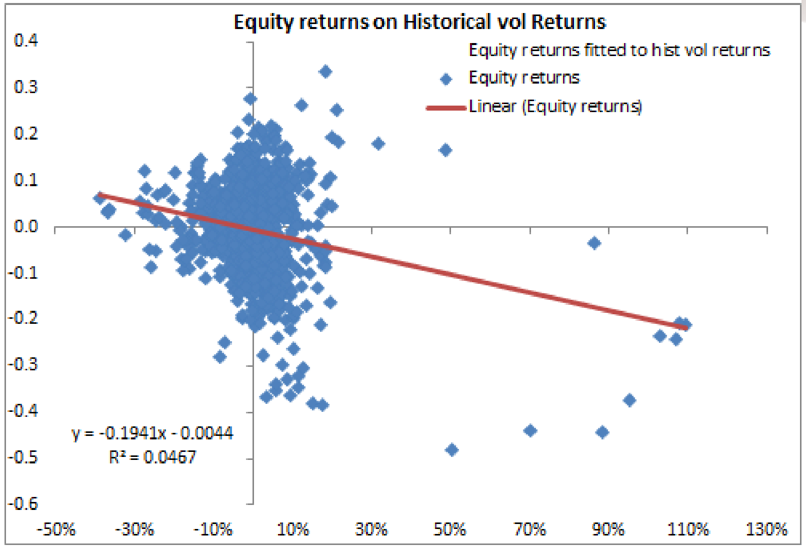


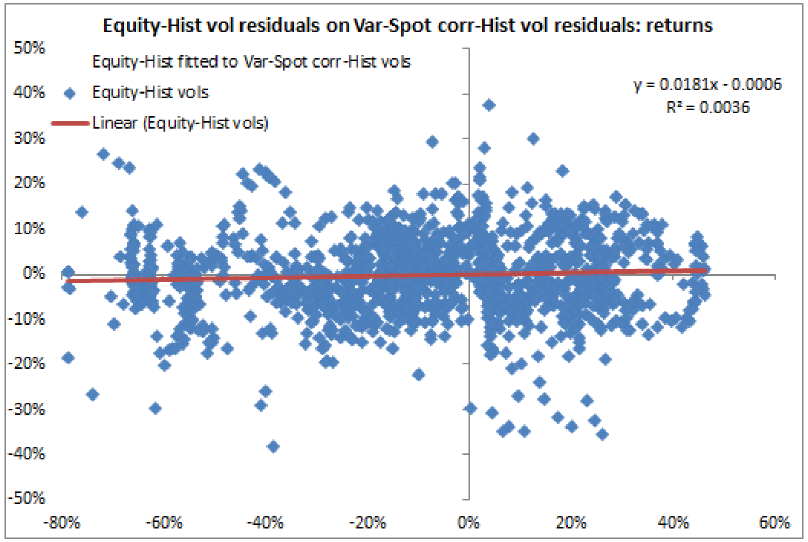


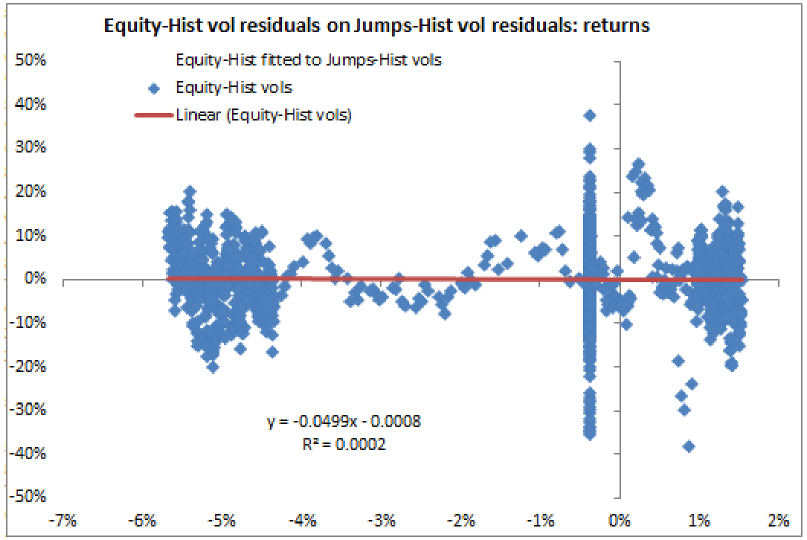


Equity and volatility (II): returns on returns - historical

- Hardly any dependence: median R^2 is 3% for historical vol returns, increasing to 4% with either one of the two historical skew proxies
- Very similar numbers for more liquid names
- Same situation as for CDS returns
- Regressions shown for Toshiba Corporation





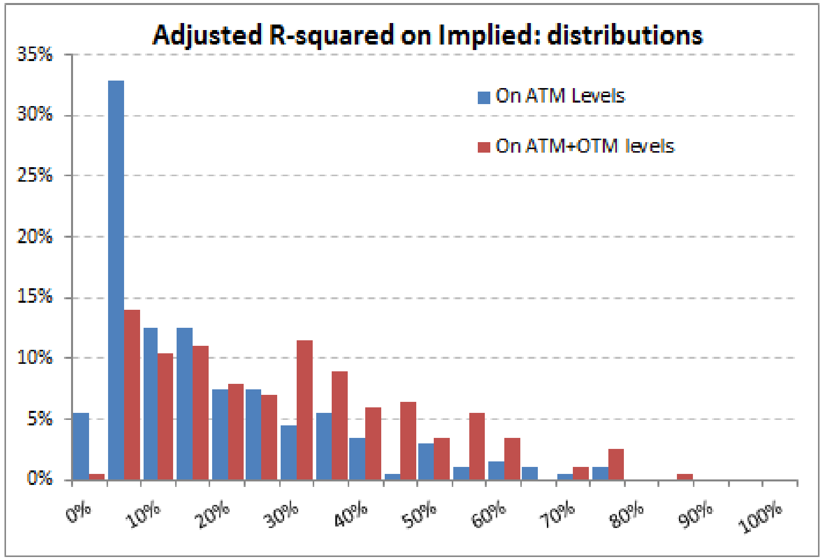


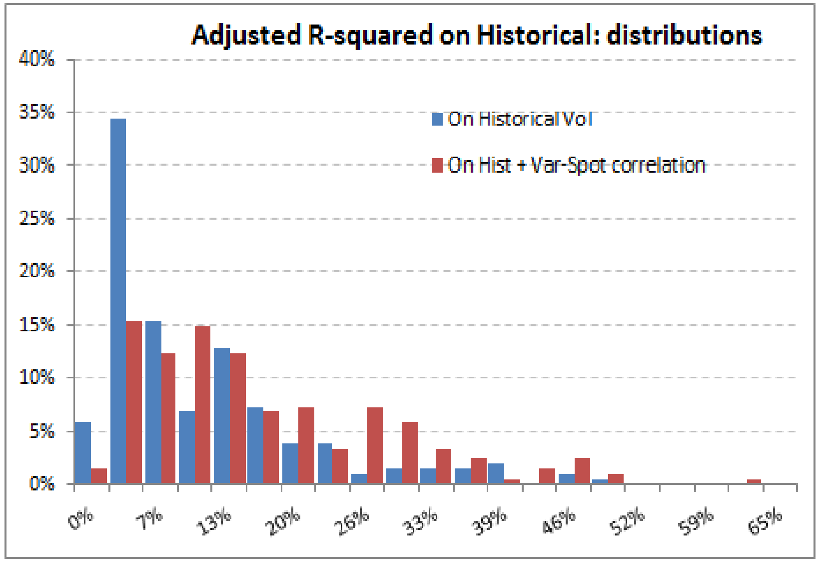
Missing: equity levels on volatility levels?

- CDS spread analysis demonstrates that levels regress much better than returns, especially when historical vols are used
- <u>Problem</u>: equity prices are meaningless for OLS regressions!
  - Dispersion across markets and currencies, no uniform base for comparison
  - Equity price time series are non-stationary, so spurious regression likely
- Can we take a stab at designing a synthetic “equity level”?
- Step back: why are equity prices not meaningful?
  - Share price is not a good indicator of a company’s “investor value”: doubling the firm’s assets and liabilities will increase share price, but not reduce its riskiness
  - CDS spreads (price of default risk) don’t have this “size effect”, nor do equity returns
- <u>Idea</u>: come up with an appropriately *normalised share price*, to make the measure comparable across different types and sizes of companies
- <u>Proposal</u>: divide share price by the price of the index it belongs to
  - Better statistical properties of the time series expected
  - Market cap weighting helps: normalisation brings companies to more equal footing
- Statistical tests show improvement in stationarity, although not for all names and indices (could be due to index weighting rules?)

"Equity levels" on volatility levels regressions

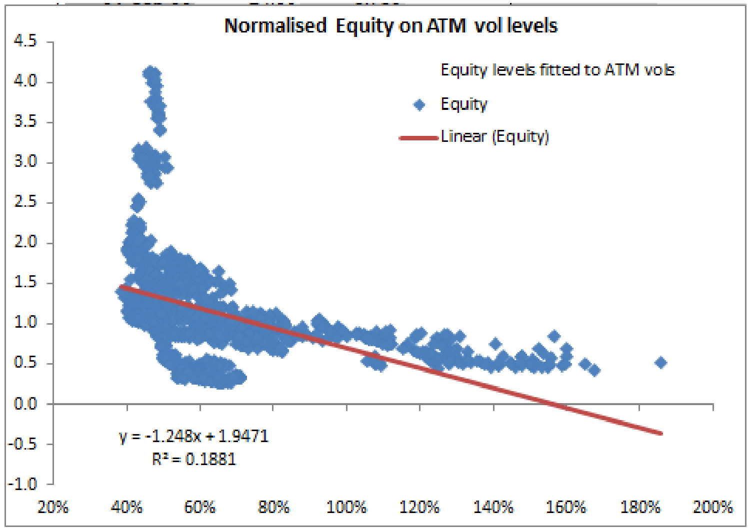
- Performed on a subset of ca. 200 names with near-stationary "equity levels"
- See improved R^2 over historical vol returns, but not over implied vol returns:
  - Median R^2 is 9% for implied ATM vols and 11% for historical, increasing to 13.5% with OTM vol and to 14.5% with variance-returns correlation or jumps (not shown)
  - Compare with 30% median R^2 for equity returns on ATM vol returns, 3-4% R^2 on historical vol returns, and no effect of skew or its proxies
  - Still smaller than the "levels" regression for CDS spreads
- Note: no information on direction of price moves, so slope can have any sign

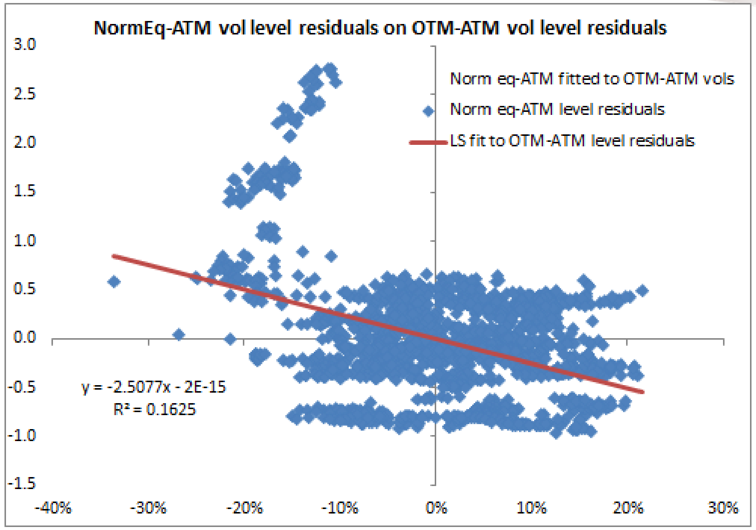




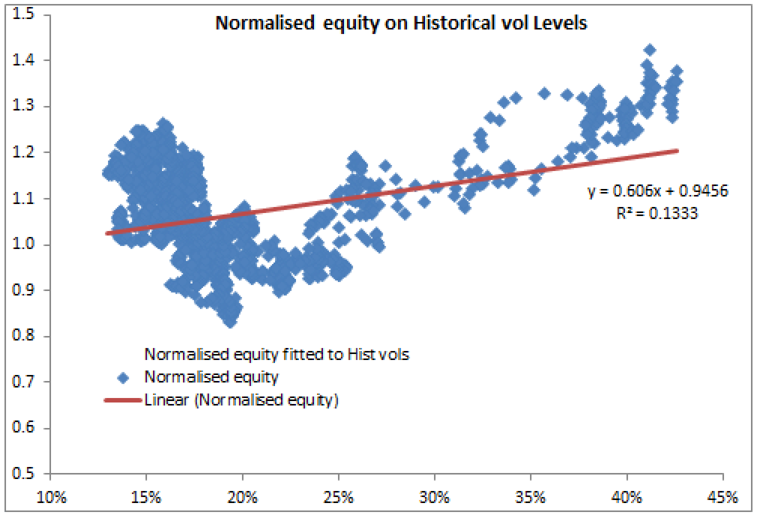
Equity levels on volatility levels: examples

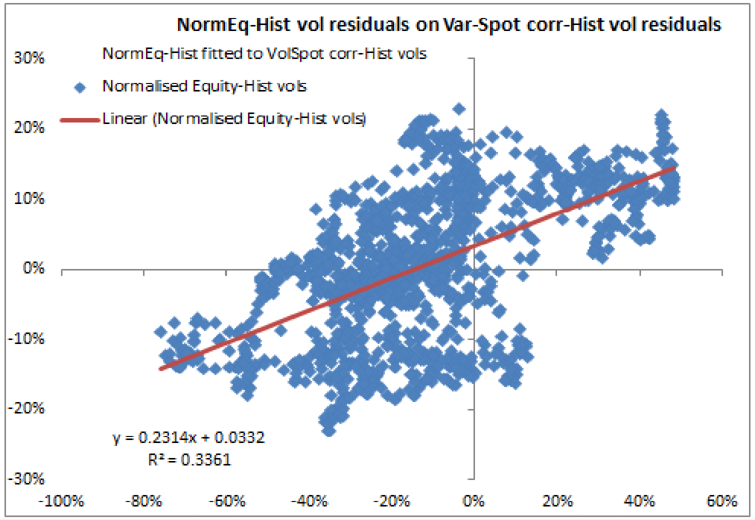
Implied:
AMD





Historical:
Verizon





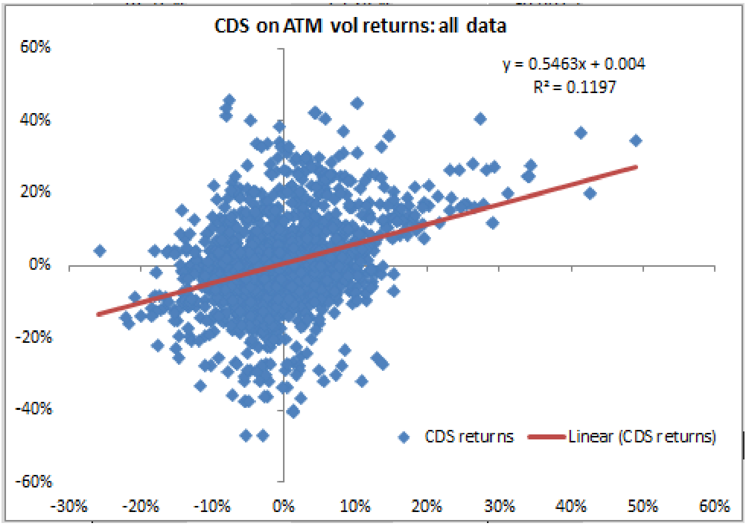
Tail regressions

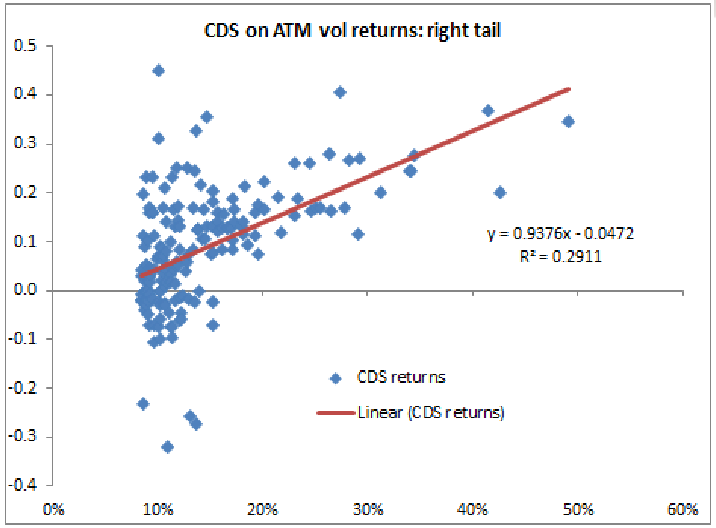
- Dependence of extreme returns can differ from “normal” returns
  - For example, even low-correlated names can start dropping together in a crisis
- We perform regressions on the top and bottom 10% returns only, and compare with main results (“central” return scenarios)
  - One tail at a time, to avoid artificial “R^2 inflation”
  - Use CDS-on-vol returns as an example
  - Look for a pattern such as the one shown on the next slide

- Some evidence of different dependence strength observed
  - More of high R^2’s in the “right tail”: stronger dependence between high vol returns and high CDS spread returns, especially for historical vols
  - More of low R^2’s in the “left tail”: weaker dependence between low returns
  - Consistent with the “crisis” intuition, but median R^2 still only goes up to ~10%
    - CDS on implied vol returns: from 7.7% for all returns to 10.3% for high returns
    - CDS on historical vol returns: from 2.5% for all returns to 10.5% for high returns
- Fact: linear models are not very good at capturing tail dependence…

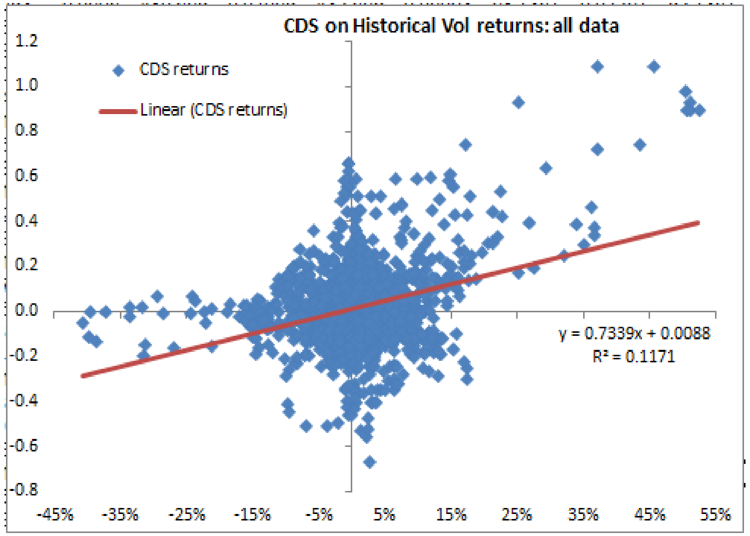
CDS spread returns on volatility return tails: examples

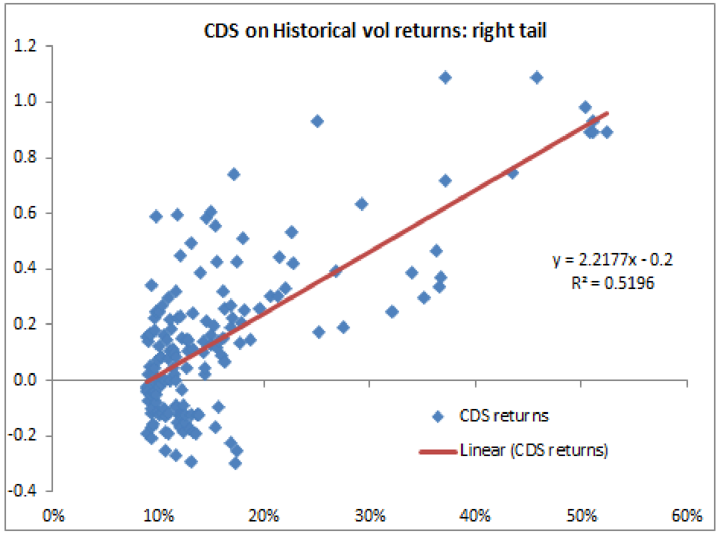
Implied:
BAT





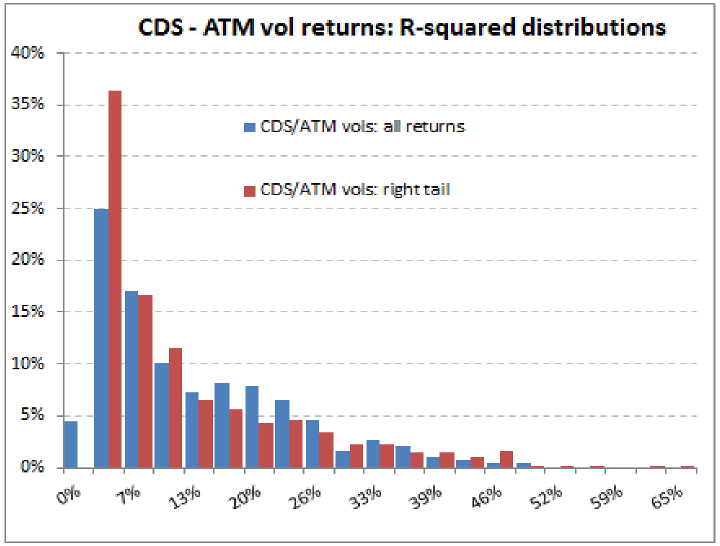
Historical:
Heidelberg
Cement

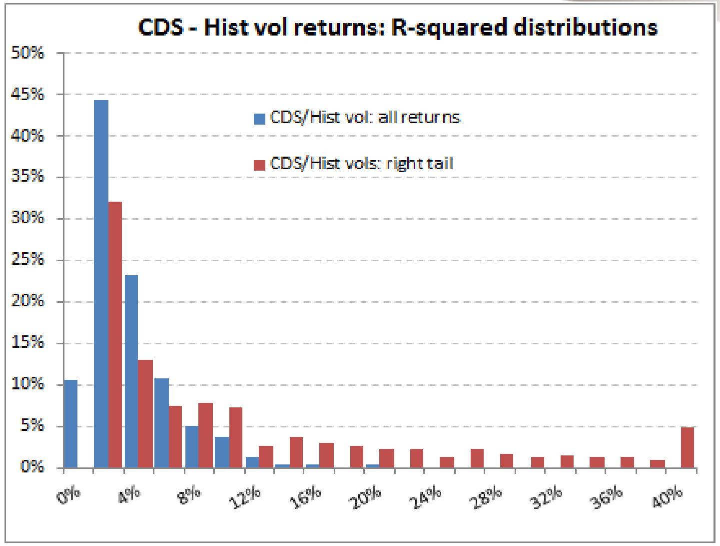




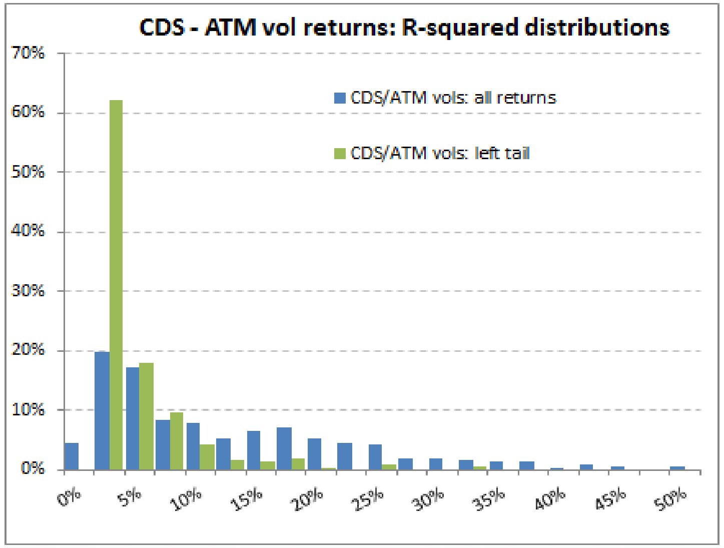
CDS spread returns on volatility return tails: R^2 distributions

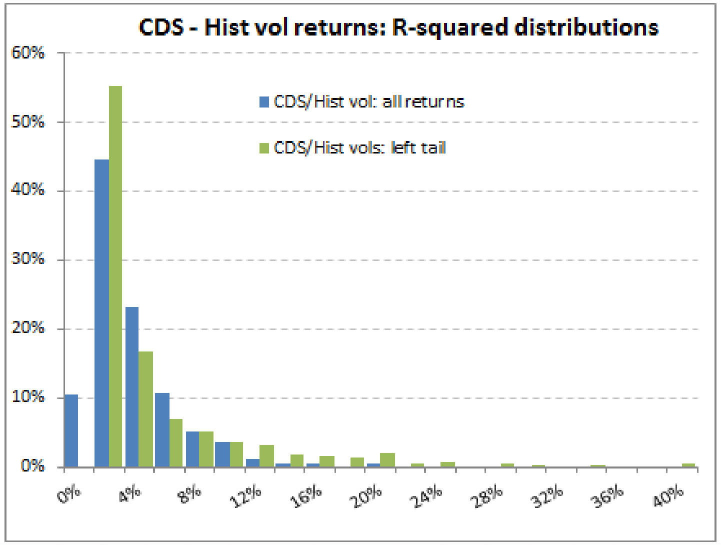
Right tail
(high returns)





Left tail
(low returns)





Volatility as a common driver: conclusions

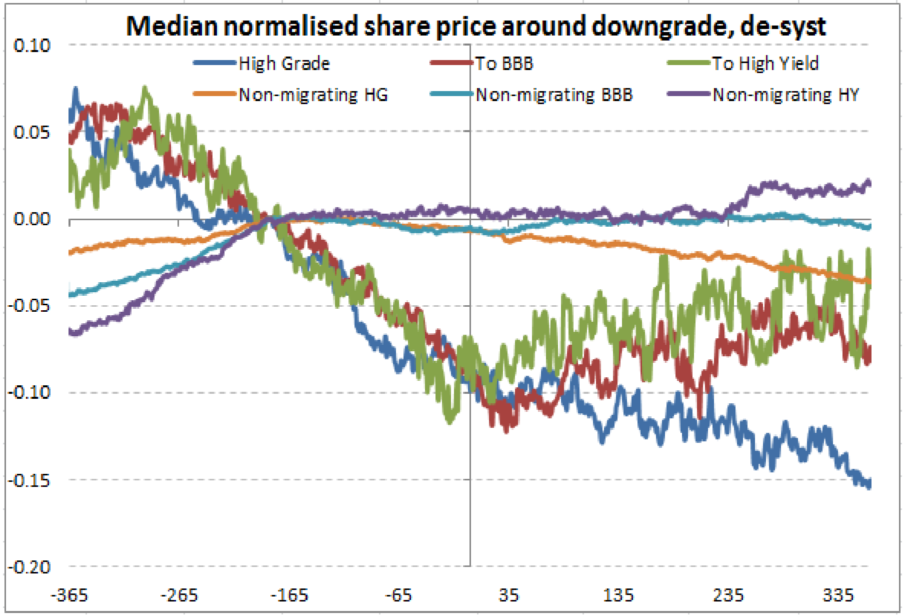
- We found some evidence of dependence between volatility and both CDS spreads and equities
  - Strongest for ATM vols
  - Better for CDS levels than for returns
- Some valuable information gathered
  - Dependence between levels can be useful for longer-term links (although not quite working for equity)
  - Confirmation of change in the dependence for extreme returns (although need a better model to capture it properly)
- Overall, the dependence is generally not strong enough to build a model around
  - Weakest for historical vols, which has the most importance for risk models
- Cannot reliably conclude that volatility can be modelled as a common driver behind equity and credit underlyings
- Unlikely that the situation is any better in the tails…
- Volatility as a guide to equity modelling language (jumps vs. correlation) - some indicative findings in favour of jumps

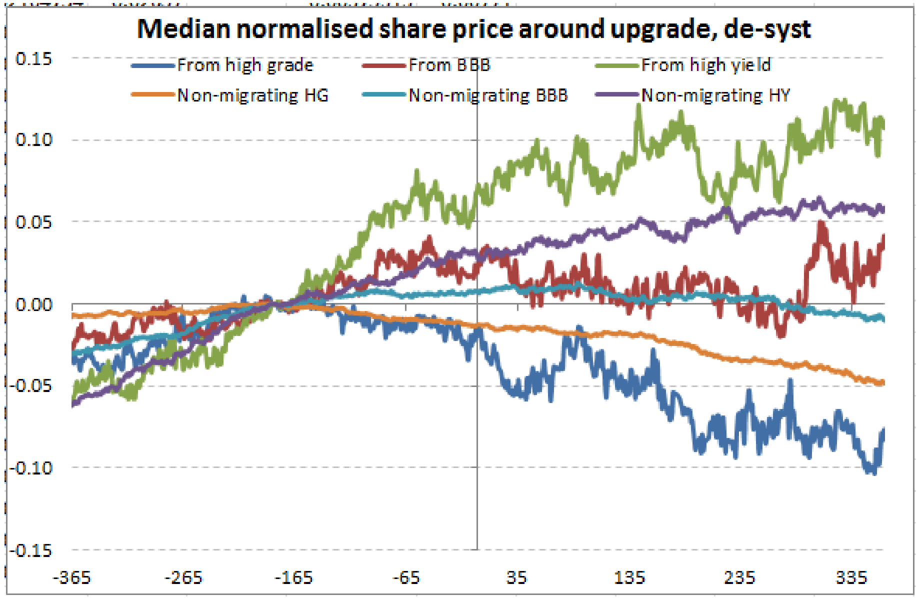
What next? (preview)

- "New flavour" did not work, so back to the standard common driver: Merton
- Structural approach: credit and equity are driven by asset returns
  - Merton: equity = call, debt = put on a firm's assets
- Ratings: convenient discretisation…
  - Moody's KMV and similar: ratings change when asset returns cross thresholds
  - Historical transition probability tables provide a calibration vehicle for discretised asset return models
- … or a fundamental property of asset return evolution?
  - Are asset return dynamics continuous or event driven?
  - Does the market take ratings into account or are they arbitrary discretisations?
- Question: how do share prices and credit spreads react to rating migrations?
  - Agency rating actions are likely to trail the market
  - Need to observe behaviour before and after downgrades and upgrades
- Centring around the migration event, look at averaged share price, CDS spread and implied volatility behaviour
- As next pages indicate, agency rating changes are clearly reflected in the behaviour of market parameters (driving event)

Share price dynamics around rating migrations

- Downgraded names – "hockey stick" pattern: negative drift before, stable after
- Starts approximately 9 months before the event



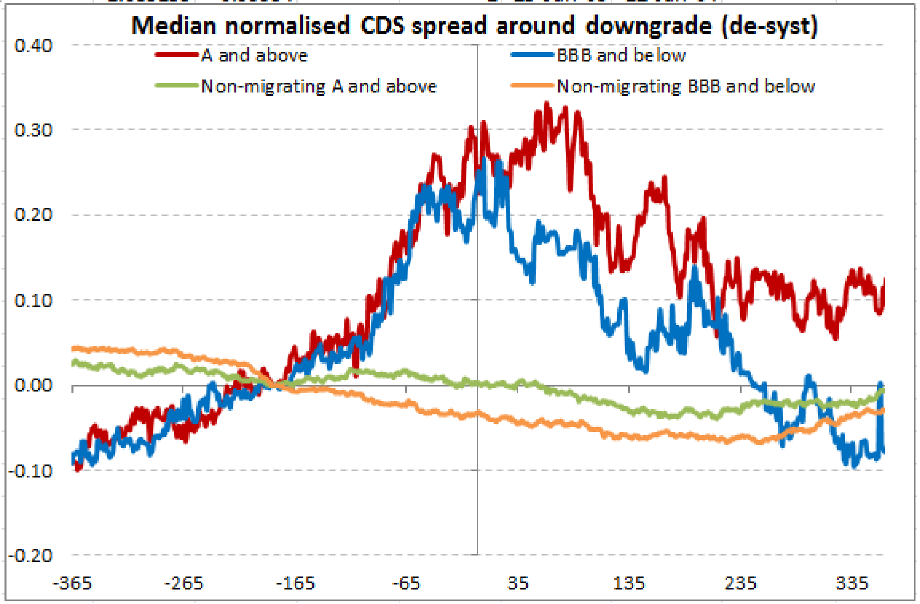


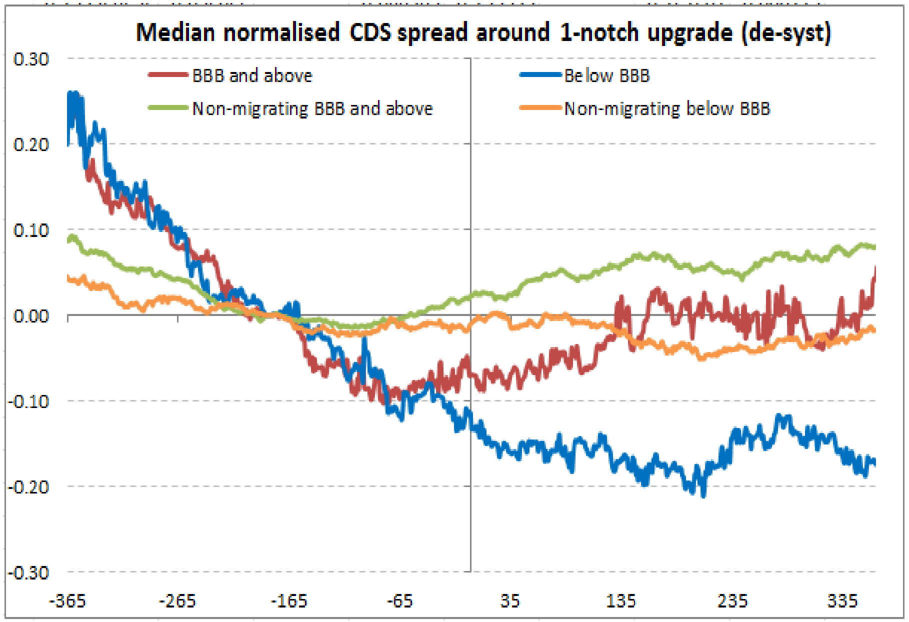
- Upgraded names: smaller upward drift before, largely stable after
- Timing less clear, possibly a slower and/or weaker effect
- "Risk-return" pattern after the event decreases if "de-systematised" per rating band

* "De-syst" means that market average has been subtracted

CDS spread dynamics around rating migrations

- Downgraded names – “hat” pattern: spreads rise before, drop after
- Post-downgrade level higher, reflecting increased credit risk

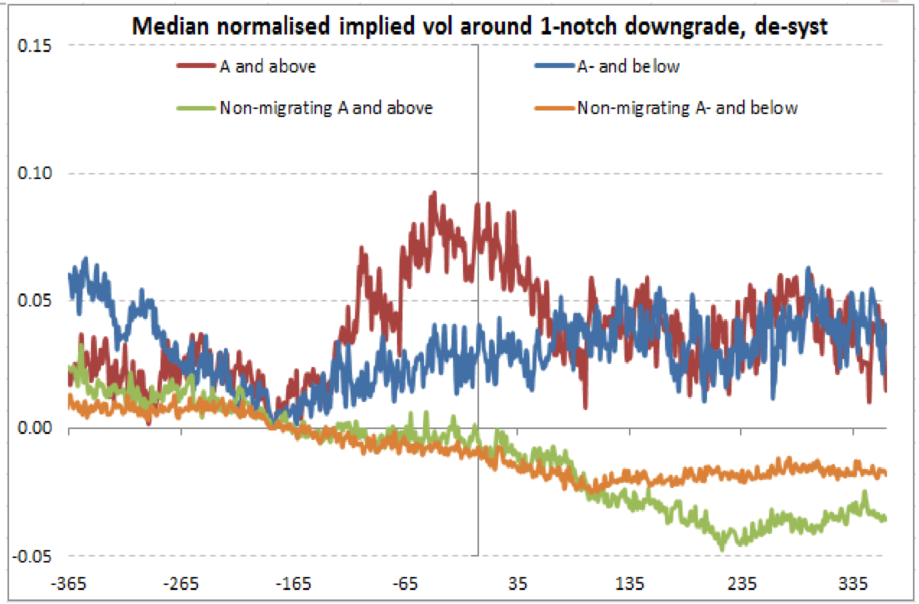


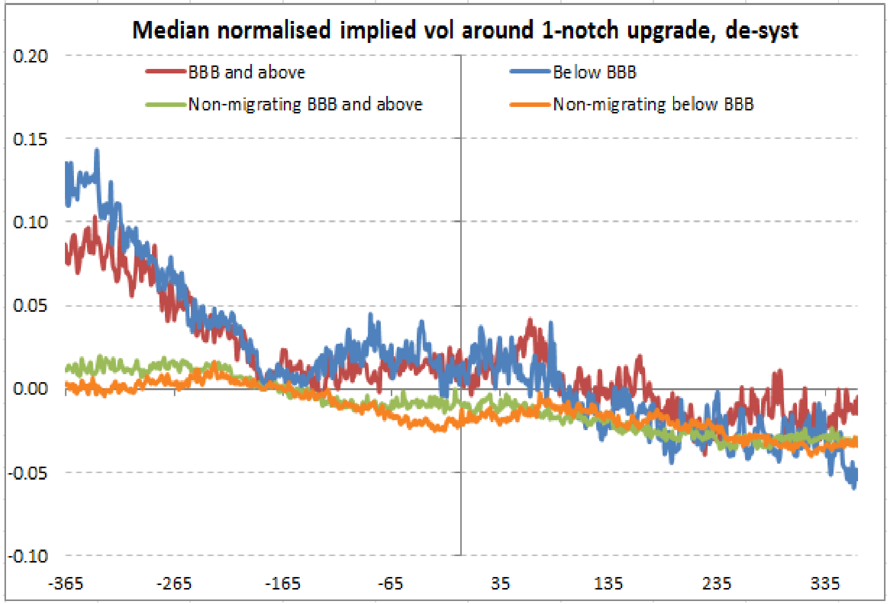


- Upgraded names: less clear, some hybrid of “hockey stick” and “hat” patterns
- Signal weaker overall

Implied volatility dynamics around rating migrations

- Downgraded names: similar to CDS (“hat” pattern), stronger for highly rated names
- Some unexpected pre-event drifts detected as well

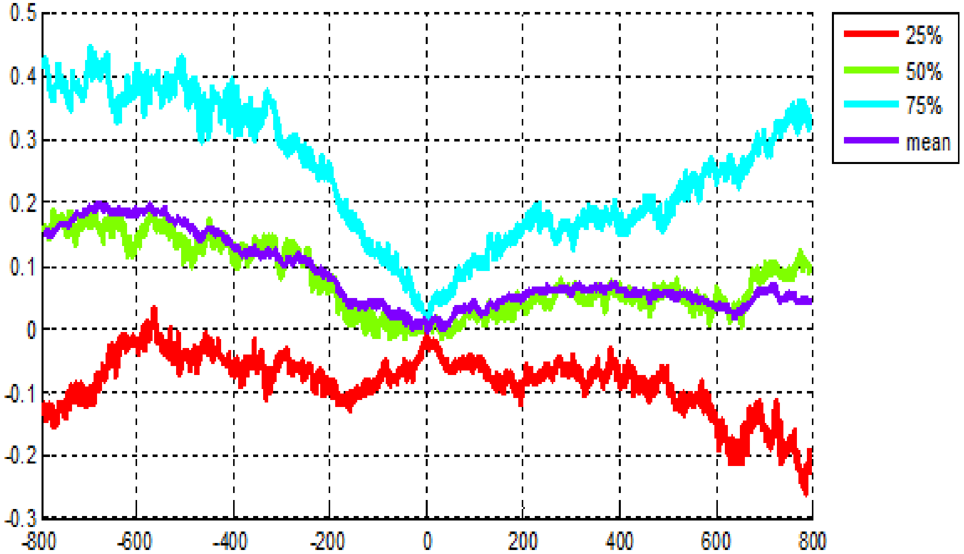


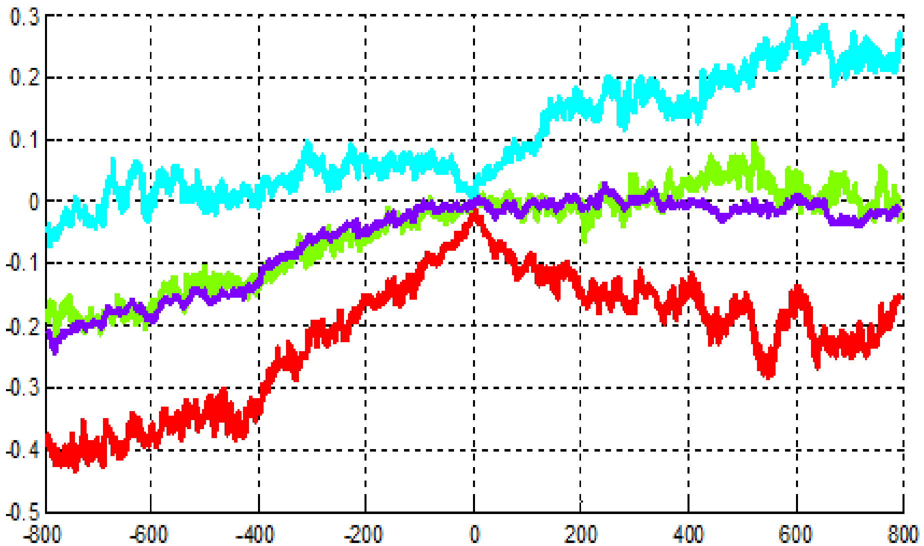


- Upgraded names: “hockey stick” pattern, implied vol dropping and staying low through the event

Asymmetry in the market?

- Share price reactions to downgrades vs. upgrades appears to differ in strength
  - Downgrades preceded by 6-9 month of negative drift, ~20% annualised
  - Positive drift before upgrades less significant, at most 5% p.a. over the same period
- Bad news for Merton's model?
  - Example: consecutive rating changes of up 1 notch, then down 1 notch, vs. down 1 notch, then up 1 notch
  - Should come back to the same price in the model – but not in the market?
- Evidence over longer term (3-5 years) - Merton model takes over





Conclusions

- Modelling credit-equity dependence is a multifaceted beast
  - Model returns or levels
  - Use market-implied or historical data
  - Via correlation or common driver
  - Look at all returns or only extreme ones separately
- Merton's idea presents several candidates for a common driver
  - Asset returns
  - Volatility, due to optionality in both debt and shares
- Volatility does not perform well as common driver behind equity and credit
  - Some dependence pattern discovered, but overall weak
- Classical structural link may work better
  - Initial analysis based on rating migrations shows promising patterns
  - Strong evidence to support event-driven dynamics for asset returns

Acknowledgements

- Thanks to Erdem Ultanir, Lee Moran, Vera Minina, Mirela Predescu, Jean-Baptiste Brunac, Cecile Barthelemy and Rim Tehraoui for their input at various stages of this work.

Disclaimer

The views expressed by authors in this presentation are their own and do not necessarily reflect the views of BNP Paribas.

This presentation is for information and illustration purposes only. It does not, nor is it intended to, constitute an offer to acquire, or solicit an offer to acquire any securities or other financial instruments.

This document does not constitute a prospectus and is not intended to provide the sole basis for any evaluation of any transaction, securities or other financial instruments mentioned herein. To the extent that any transactions is subsequently entered between the recipient and BNP Paribas, such transaction will be entered into upon such terms as may be agreed by the parties in the relevant documentation. Although the information in this document has been obtained from sources which BNP Paribas believes to be reliable, BNP Paribas does not represent or warrant its accuracy and such information may be incomplete or condensed.

Any person who receives this document agrees that the merits or suitability of any transaction, security or other financial instrument to such person's particular situation will have to be independently determined by such person, including consideration of the legal, tax, accounting, regulatory, financial and other related aspects thereof. In particular, BNP Paribas owes no duty to any person who receives this document (except as required by law or regulation) to exercise any judgement on such person's behalf as to the merits or suitability of any such transaction, security or other financial instruments. All estimates and opinions included in this document may be subject to change without notice. BNP Paribas will not be responsible for the consequences of reliance upon any opinion or statement contained herein or for any omission.

This information is not tailored for any particular investor and does not constitute individual investment advice. This document is confidential and is being submitted to selected recipients only. It may not be reproduced (in whole or in part) or delivered to any other person without the prior written permission of BNP Paribas.