The imprecision of volatility indexes

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  3. Trading strategies: make decisions to switch between positions.
  4. Hedging tool: using VIX based derivatives.
     CBOE introduced VIX futures in 2004 and options in 2006.
     In 2012, open interest for futures at 326,066 and options at 6.3 million contracts.

VIX is imprecise!

Example: Vega VIX

In our sample, the size of the 95% confidence band for Vega VIX (VVIX) is 2.9 percentage points in the median case.

Concern about imprecision in a VIX estimator arises due to aggregation of imprecise implied volatilities (IVs). Latane and Rendleman, 1976; Hentschel, 2003; Jiang and Tian, 2007

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1. Imprecise option prices.
   - Example: A 6100 OTM call option on the Nifty index is priced at Rs.1.92 when using a VVIX of 17.82%.
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2. Imprecise VaR and portfolios based on it.
3. Difficulty with pricing derivatives on a fuzzy underlying.

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- Estimate the imprecision of model based VIXs.
- Use bootstrapping to estimate the imprecision in a VIX estimator.
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- Imprecision indicators are used for model selection:
  vega, liquidity, and elasticity weighted VIXs.
- VVIX has the lowest imprecision with a median CI width of 2.9pp.

Outline

- Concerns about measurement
- Measuring the imprecision in a VIX
- Two empirical examples
- Using this measure of imprecision for model selection
- Imprecision of VIX as a measure of ambiguity
- Conclusion

Concerns about measurement

Two approaches to measurement

- Model based approach - uses option pricing model - VXO, VEGA VVIX etc.
  - Measurement errors in prices - imprecise IVS (Hentschel, 2003)
  - Hentschel (2003) derives CI's from B-S formula.
  - For an ATM stock option with 20 days to expiry, the 95% CIs are of the order +/- 6 pp.
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  - For an ATM stock option with 20 days to expiry, the 95% CIs are of the order +/- 6 pp.
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- Model free approach - pricing of variance swap - CBOE VIX
  - Methodological errors (Jiang and Tian, 2005)
  - Imprecise intra-day VIX due to varying strike range (Andersen et al., 2011)

Measuring the imprecision in a volatility index

Our approach to the problem

- Non-parametric methodology; contrast with Hentschel (2003).
- Model based; contrast with model free.
- Agnostic about the distribution of errors.
- Each option price is an imprecise transformation of the true implied volatility index.
- Bootstrapping to estimate the imprecision in the VIX estimator.

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2. Computation of the average weighted IV for each maturity i:

$$IV_i = \frac{\sum_{j=1}^{n} w_{ij} IV_{ij}}{\sum_{j=1}^{n} w_{ij}}$$

where, IV_{ij} refers to a vector of IVs for $j = \{1 \ldots n\}$ and two nearest maturities, $i = \{near, next\}$, w_{ij} refers to the vega weight for the corresponding IV_{ij}.

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3. The vega weighted average IVs are interpolated to compute the 30 day expected volatility, VVIX.

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- The parallel with LIBOR suggests a bootstrap inference approach for VVIX.

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7. Now, compute:
   - Standard deviation (σ)
   - Confidence bands – adjusted bootstrap percentile method (Efron, 1987)

Data description

- S & P 500 index (SPX) options end-of-day data.
- The data is available for the months of Sep, Oct, and Nov 2010.
- Nifty options tick-by-tick data ($\sim$ 200K obs. per day):
- The data is available from Feb, 2009 to Sep, 2010.
- Each dataset includes:
  - Transaction date
  - Expiry date of the options contract
  - Strike price
  - Type of the option i.e. call or put
  - Price of the underlying index
  - Best buy price and ask price of option
- The one and three month MIBOR rates provided by NSE as the riskfree rates.
- The one and three month US Treasury bill rates provided by the US department of the Treasury as the riskfree rates.

Sampling procedure

- We follow Andersen et al. (2011) and sample options as follows:
  1. Construct fifteen seconds series for each individual option using the *previous tick method* from tick-by-tick data.
  2. Retain the last available quotes prior to the end of each fifteen second interval throughout the trading day.
  3. If no new quote arrives in a fifteen second interval, the last available quote prior to the interval is retained.
  4. If no quote is available in the previous interval, the last available quote from the last five minutes is retained.
  5. Filter out options with zero traded volume (optional).
- For robustness check, sampling frequencies of thirty and sixty seconds are also used.

Two empirical examples

Intuition

- We use a sample of near-the-money SPX options.

The underlying is at 1125.59, the number of days to expiry is 29 and the risk-free rate is 0.12%.

Strike	Type	Mid-Quote	IVol (%)	Strike	Type	Mid-Quote	IVol (%)
1095	c	42.50	19.31	1095	p	14.00	21.29
1100	c	38.00	18.30	1100	p	15.25	20.87
1105	c	35.25	18.71	1105	p	16.65	20.48
1110	c	31.75	18.35	1110	p	18.05	19.99
1115	c	28.60	18.14	1115	p	19.70	19.59
1120	c	25.75	18.05	1120	p	21.55	19.24
1125	c	22.75	17.70	1125	p	24.55	19.68
1130	c	19.35	16.90	1130	p	26.30	19.00
1135	c	16.85	16.66	1135	p	28.10	18.22
1140	c	14.00	15.98	1140	p	30.85	18.05
1145	c	12.35	16.12	1145	p	33.65	17.79
1150	c	10.50	15.94	1150	p	36.45	17.37
1155	c	8.55	15.49	1155	p	39.75	17.22

Note: We define near-the-money-options as call and put options with strike-to-spot ratio between 0.97 and 1.03 (Pan and Poteshman, 2006).

- 95% CI of sample mean: [17.65, 18.84]

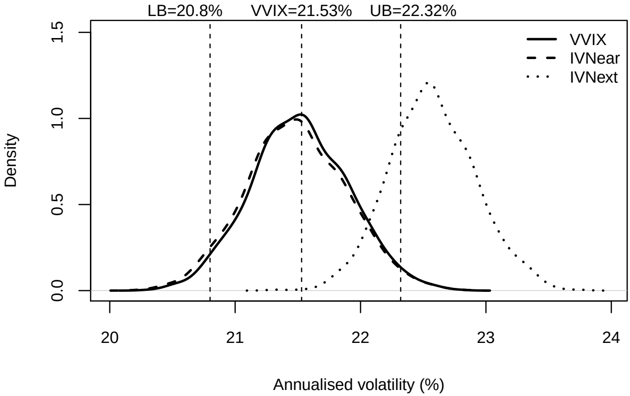
A sample of SPX options

```
     Strike Type Underlying Mid-Quote Maturity Risk-free  IVol
  1:    965    c    1125.59    160.70       29      0.12 18.02
  2:    970    c    1125.59    155.85       29      0.12 21.87
  3:    975    c    1125.59    150.85       29      0.12 21.19
  4:    980    c    1125.59    146.00       29      0.12 22.29
  5:    985    c    1125.59    141.00       29      0.12 21.57
 ---
383:   1400    p    1125.59    278.35       64      0.16 33.14
384:   1450    p    1125.59    328.40       64      0.16 37.27
385:   1500    p    1125.59    378.15       64      0.16 40.61
386:   1550    p    1125.59    428.25       64      0.16 44.41
387:   1600    p    1125.59    478.10       64      0.16 47.53
```

A single replicate

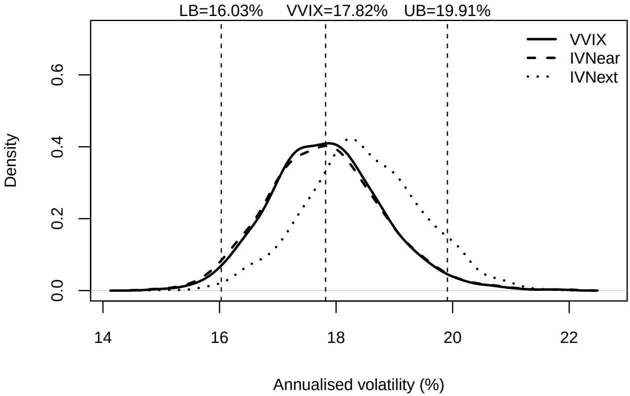
```
     Strike Type Underlying Mid-Quote Maturity Risk-free  IVol
  1:    680    p    1125.59      0.08       29      0.12 61.16
  2:   1055    c    1125.59     75.55       29      0.12 21.58
  3:   1070    p    1125.59      8.85       29      0.12 23.04
  4:    900    p    1125.59      0.78       29      0.12 38.44
  5:   1245    p    1125.59    121.10       29      0.12 22.54
 ---
383:   1050    p    1125.59     18.00       64      0.16 25.56
384:   1005    c    1125.59    127.55       64      0.16 23.76
385:   1110    c    1125.59     45.30       64      0.16 19.72
386:    955    c    1125.59    172.95       64      0.16 23.74
387:    880    p    1125.59      3.00       64      0.16 35.52
```

The distribution of VVIX on 2010-09-17: SPX



The one-day change in VVIX is smaller than 1.5pp on 62% of the days.

The distribution of VVIX on 2010-09-01: Nifty



The one-day change in VVIX is smaller than 4pp on 92% of the days.

Imprecision of VVIX over a large sample of Nifty options

- The imprecision indicators are computed from Feb 2009 to Sep 2010.
- The median CI for VVIX is 2.9pp which is an economically significant one.
- This is larger than the one-day change in VVIX of 1.18pp.

Using this measure of imprecision for model selection

Benchmarking performance of VIXs

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- Precision is desirable in an estimator.
- Smaller σ and confidence interval $\implies$ higher precision.

Methodology

- Competitors:
  - Vega weighted VIX: VVIX
  - Liquidity weighted VIX: SVIX, TVVIX
  - Elasticity weighted VIX: EVIX
- Period of analysis: February 2009 - September 2010.
  Four snapshots a day.
- Sampling frequency: 15, 30, and 60 seconds.

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  Four snapshots a day.
- Sampling frequency: 15, 30, and 60 seconds.
- Performance indicators: σ and width of CI.
- Significant test: Pair wise Wilcoxon signed rank test.
- VVIX has the highest precision – median CI width of 2.90pp and σ of 0.73pp.
- Presented results are for 15 seconds.
  The results are robust to the sampling frequency.

Summary statistics

	SVIX	TVVIX	VVIX	EVIX
Size of confidence band (pp)				
Min	0.929	1.362	1.033	2.177
1st Qu	2.713	2.743	2.271	6.201
Median	3.546	3.418	2.923	7.368
Mean	4.542	4.024	3.907	8.245
3rd Qu	4.845	4.440	4.064	9.262
Max	52.940	23.790	50.490	51.080
Std Dev	3.803	2.109	3.636	3.926
σ of the bootstrap estimates (pp)				
Min	0.239	0.344	0.255	0.571
1st Qu	0.706	0.706	0.581	1.576
Median	0.913	0.877	0.739	1.868
Mean	1.139	1.028	0.945	2.053
3rd Qu	1.252	1.141	1.025	2.324
Max	13.390	4.772	11.780	10.580
Std Dev	0.822	0.530	0.754	0.875

Pairwise comparisons: Wilcoxon sign rank test

	Size of confidence band		σ of the bootstrap estimates	
	Median Diff	Pval	Median Diff	Pval
EVIX - SVIX	3.745	0.000	0.923	0.000
EVIX - TVVIX	3.846	0.000	0.962	0.000
EVIX - VVIX	4.326	0.000	1.097	0.000
SVIX - TVVIX	-0.004	1.000	0.013	0.341
SVIX - VVIX	0.641	0.000	0.183	0.000
TVVIX - VVIX	0.618	0.000	0.165	0.000

Ranking: VVIX, SVIX & TVVIX, EVIX

Imprecision of VIX as a measure of ambiguity

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  3. Ehsani et al. (2013) use the mean divergence between implied probability distributions.
- The proposed measure of imprecision of VIX, might prove to be useful in quantifying the extent of ambiguity that is present at a point in time.

Reproducible research

R package ifrogs has been released into the public domain, with an open source implementation of the methods of this paper.

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- Imprecision in VIX is significant – estimated from SPX or Nifty options.
- Use the imprecision indicators for model selection.
  VVIX is the most precise estimator.

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  1. a model-free strategy
  2. free from any distributional assumptions about errors
  3. a large sample of options
  4. a VIX derived from a wide range of strikes in contrast to VXO
- Imprecision in VIX is significant – estimated from SPX or Nifty options.
- Use the imprecision indicators for model selection.
  VVIX is the most precise estimator.
- Future work:
  Use imprecision indicators to measure ambiguity.
  Inference procedures for model-free estimators such as the CBOE VIX.

Thank you