

# Exploiting the Errors: A Simple Approach for Improved Volatility Forecasting

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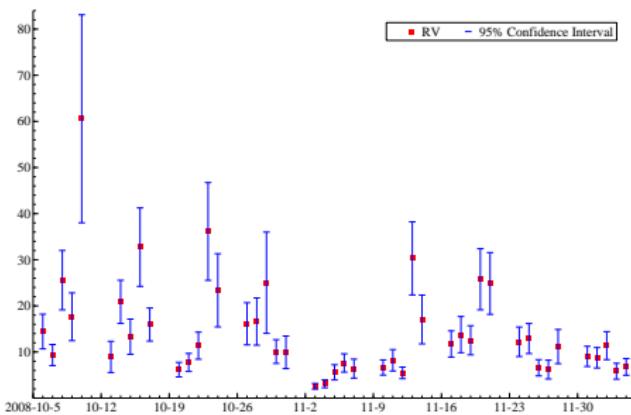
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- Realized Volatility (RV) based modeling and forecasting procedures have become very popular
  - ARFIMA (Andersen, Bollerslev, Diebold and Labys, 2003)
  - HAR-RV (Corsi, 2009)
  - ...
- Generally superior to standard GARCH and Stochastic Volatility (SV) models
  - And much easier to estimate and implement ...
- Effective way of incorporating (the relevant) information in high-frequency data into the forecasts
  - Only minor efficiency loss (Andersen, Bollerslev and Meddahi, 2004)
  - Built-in robustness (Sizova, 2011)

- Most realized volatility-based forecasting models effectively treat the volatility as directly observable
  - But, RV still subject to non-trivial measurement errors ...



- The quality of the forecasts need to be properly interpreted
  - $R^2$  adjustments (Andersen, Bollerslev and Meddahi, 2005)
  - Ranking criteria (Patton, 2011)

- Instead of adjusting the measures of the quality of the forecasts, we **adjust the forecasts** themselves
- Our adjustments rely on the asymptotic distribution theory for RV and the **heteroskedasticity** of the measurement errors (Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002)
- Simple and easy-to-implement modification of the popular HAR-RV model: **HARQ**
- The HARQ model performs well in simulations
- The HARQ model beats a challenging set of benchmark models when applied to the S&P 500 and a large set of individual stocks

- Log-price process:

$$d \log(P_t) = \mu_t dt + \sigma_t dW_t$$

- Could easily allow for jumps
- Daily **latent** Integrated Volatility (**IV**) of interest:

$$IV_t \equiv \int_{t-1}^t \sigma_s^2 ds$$

- Consistently ( $\Delta \rightarrow 0$ ) estimated by Realized Volatility (**RV**):

$$RV_t \equiv \sum_{i=1}^{1/\Delta} r_{t,i}^2$$

where  $r_{t,i} \equiv \log(P_{t-1+i\Delta}) - \log(P_{t-1+(i-1)\Delta})$

- Suppose daily IV follows a simple AR(1):

$$IV_t = \phi_0 + \phi_1 IV_{t-1} + \epsilon_t$$

- By standard arguments  $RV_t \equiv IV_t + \eta_t$  follows ARMA(1,1)
- Suppose the researcher estimates an AR(1) for RV:

$$IV_t + \eta_t = \beta_0 + \beta_1 (IV_{t-1} + \eta_{t-1}) + \epsilon_t$$

- Attenuation bias** with *i.i.d.* measurement errors:

$$\beta_1 = \phi_1 \left( 1 + \frac{\sigma_\eta^2}{Var(IV_t)} \right)^{-1}$$

- But, the measurement errors are **heteroskedastic**:

$$RV_t = IV_t + \eta_t, \quad \eta_t \sim N(0, \sigma_{\eta,t}^2)$$

where  $\sigma_{\eta,t}^2 = 2\Delta IQ_t$  and  $IQ_t \equiv \int_{t-1}^t \sigma_s^4 ds$

- Allow the AR(1) coefficient to **vary** with  $\sigma_{\eta,t}^2$ :

$$\beta_{1,t} = \phi_1 \left( 1 + \frac{\sigma_{\eta,t}^2}{Var(IV_t)} \right)^{-1}$$

- $IQ_t$  (and  $\sigma_{\eta,t}^2$ ) **latent**, but consistently ( $\Delta \rightarrow 0$ ) estimated by:

$$RQ_t \equiv \frac{1}{3\Delta} \sum_{i=1}^{1/\Delta} r_{t,i}^4$$

- AR(1) coefficient depends on the inverse of  $IQ$ 
  - Non-linear estimation
- $RQ$  consistent but inaccurate estimate of  $IQ$ 
  - Inverse even more problematic
- Simple linear **time-varying** parameter **ARQ** model:

$$RV_t = \beta_0 + \beta_{1,t} RV_{t-1} + \epsilon_t$$

$$\beta_{1,t} = \beta_1 + \beta_{1Q} RQ_{t-1}^{1/2}$$

- Very easy to estimate and implement
- Built-in robustness
- Taylor series approximation

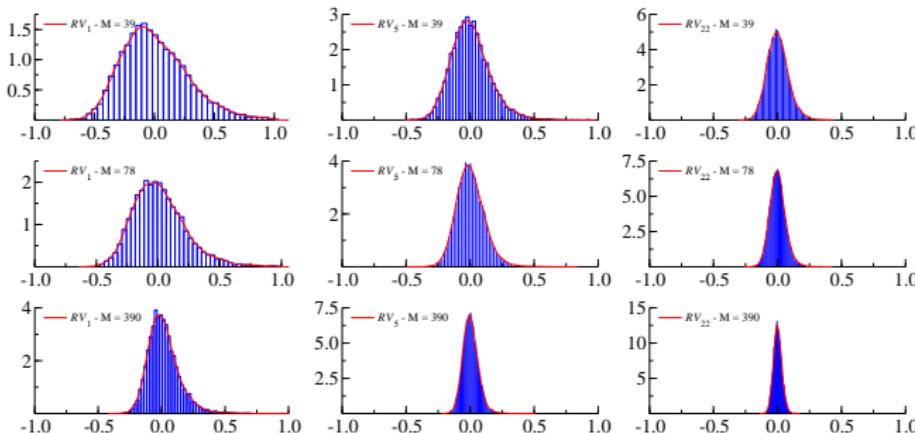
- *IV* (and *RV*) strongly persistent
  - AR(1) model too simplistic
- Heterogeneous AutoRegressive (**HAR**) model (Corsi, 2009):

$$RV_t = \beta_0 + \beta_1 RV_{t-1} + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \epsilon_t$$

- Poor man's long-memory model
- **HARQ-F (Full) model:**

$$\begin{aligned} RV_t = & \underbrace{\beta_0 + (\beta_1 + \beta_{1Q} RQ_{t-1}^{1/2})}_{\beta_{1,t}} RV_{t-1} + \underbrace{(\beta_2 + \beta_{2Q} RQ_{t-1|t-5}^{1/2})}_{\beta_{2,t}} RV_{t-1|t-5} \\ & + \underbrace{(\beta_3 + \beta_{3Q} RQ_{t-1|t-22}^{1/2})}_{\beta_{3,t}} RV_{t-1|t-22} + \epsilon_t \end{aligned}$$

- Measurement errors in  $RV_{t-1|t-h}$  decrease with **horizon** ( $h = 1, 5, 22$ ) and sampling frequency ( $1/\Delta = 39, 78, 390$ ):



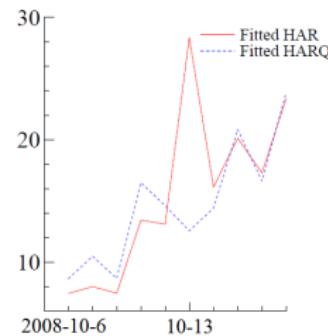
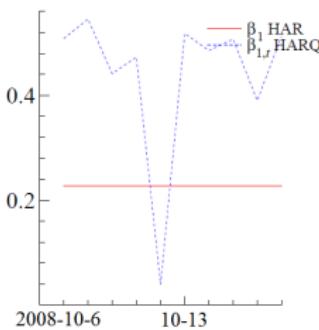
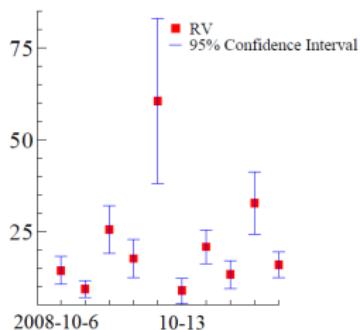
- Basic HARQ model:

$$RV_t = \beta_0 + \underbrace{(\beta_1 + \beta_{1Q} RQ_{t-1}^{1/2})}_{\beta_{1,t}} RV_{t-1} + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \epsilon_t$$

- Basic HARQ model:

$$RV_t = \beta_0 + \underbrace{(\beta_1 + \beta_{1Q} RQ_{t-1}^{1/2})}_{\beta_{1,t}} RV_{t-1} + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \epsilon_t$$

- HARQ vs HAR model estimates, S&P 500, October 2008:



# Simulation Setup

- Two-factor stochastic volatility model as in Huang and Tauchen (2005):

$$d \log P_t = \mu dt + \sigma_{ut} \nu_t \left( \rho_1 dW_{1t} + \rho_2 dW_{2t} + \sqrt{1 - \rho_1^2 - \rho_2^2} dW_{3t} \right)$$

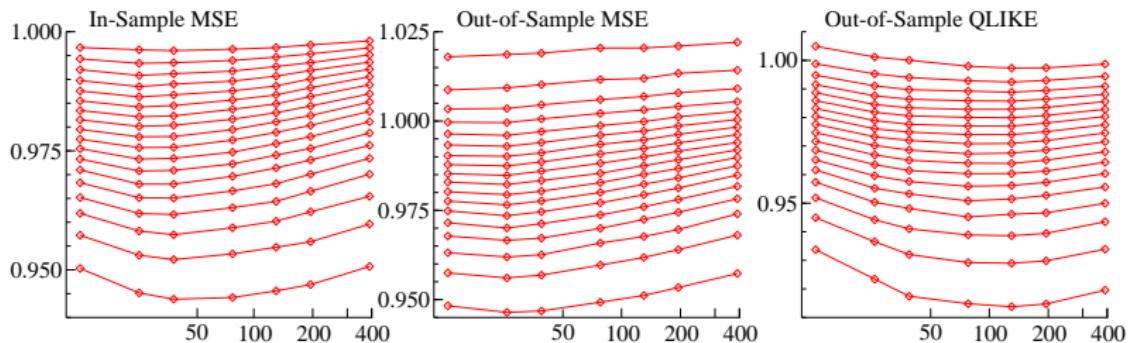
- Diurnal effects as in Andersen, Dobrev and Schaumburg (2012)
- Microstructure “noise”  $P_t^* = P_t + u_t$ ,  $u_t \sim N(0, 0.001/V_t)$ , as in Barndorff-Nielsen, Hansen, Lunde and Shephard (2008)
- Returns aggregated to 1-, 5- and 10-“minutes” ( $1/\Delta = 390, 78, 39$ )
- 1,000 replications

$$\text{MSE} : L(RV_t, X_t) = (RV_t - X_t)^2$$

$$\text{QLIKE} : L(RV_t, X_t) = \frac{RV_t}{X_t} - \log\left(\frac{RV_t}{X_t}\right) - 1$$

	AR	HAR	ARQ	HARQ	HARQ-F
M	In-Sample MSE				
39	1.0291	1.0000	0.9980	0.9773	0.9718
78	1.0285	1.0000	0.9996	0.9791	0.9735
390	1.0277	1.0000	1.0064	0.9851	0.9793
	Out-of-Sample MSE				
39	1.0438	1.0000	1.0166	0.9878	0.9900
78	1.0425	1.0000	1.0188	0.9901	0.9920
390	1.0413	1.0000	1.0268	0.9968	0.9985
	Out-of-Sample QLIKE				
39	1.0893	1.0000	1.0258	0.9680	0.9850
78	1.0881	1.0000	1.0186	0.9644	0.9821
390	1.0841	1.0000	1.0187	0.9678	0.9859

# HARQ/HAR loss ratios



**Persistence** :  $\beta_1 + \beta_2 + \beta_3$

**Mean Lag** :  $22 \frac{\sum_{i=1}^{22} i \cdot b_i}{\sum_{i=1}^{22} b_i}$

	AR	HAR	ARQ	HARQ	HARQ-F
Persistence					
39	0.4303	0.6593	0.6552	0.8132	0.9200
78	0.4568	0.6736	0.6876	0.8328	0.9449
390	0.4739	0.6803	0.6913	0.8297	0.9621
Mean Lag					
39		5.6598		4.2410	4.6956
78		5.4963		4.1026	4.5968
390		5.3685		4.1196	4.6530

# Empirical Analysis

- S&P 500 futures, Tick Data Inc.
  - April 21, 1997 - August 30, 2013
- Dow Jones individual stocks (27), TAQ
  - April 21, 1997 - December, 2013
- Five-minute  $RV$  and  $RQ$ 
  - Ameliorates the effect of market microstructure “noise”
  - Other  $RV$  and  $RQ$  estimators
- Out-of-sample forecast comparisons
  - Rolling estimation Windows (RW) (1,000 days)
  - Increasing estimation Windows (IW) (1,000-3,201 days)
  - RW and IW based on same samples

Company	Symbol	Min	Mean	Median	Max	AR	AR-IV	ARQ
S&P 500	SP500	0.043	1.175	0.629	60.563	0.651	0.953	0.983
Microsoft	MSFT	0.166	3.087	1.824	59.164	0.718	0.952	0.889
Coca-Cola	KO	0.049	2.011	1.154	54.883	0.618	0.949	0.834
DuPont	DD	0.093	3.327	2.165	81.721	0.707	0.950	0.956
ExxonMobil	XOM	0.114	2.348	1.476	130.667	0.668	0.947	0.997
General Electric	GE	0.131	3.440	1.794	173.223	0.681	0.915	0.987
IBM	IBM	0.115	2.464	1.340	72.789	0.657	0.959	0.890
Chevron	CVX	0.105	2.286	1.483	139.984	0.653	0.966	0.954
United Technologies	UTX	0.126	2.793	1.658	92.105	0.648	0.943	0.883
Procter & Gamble	PG	0.085	2.007	1.064	80.124	0.587	0.866	0.786
Caterpillar	CAT	0.207	3.810	2.401	127.119	0.727	0.954	0.896
Boeing	BA	0.167	3.371	2.147	79.760	0.630	0.936	0.822
Pfizer	PFE	0.176	2.822	1.809	60.302	0.570	0.933	0.837
Johnson & Johnson	JNJ	0.062	1.680	0.999	58.338	0.613	0.946	0.933
3M	MMM	0.140	2.278	1.358	123.197	0.495	0.952	0.748
Merck	MRK	0.127	2.758	1.718	223.723	0.372	0.913	0.708
Walt Disney	DIS	0.135	3.641	2.030	129.661	0.629	0.916	0.772
McDonald's	MCD	0.090	2.678	1.680	130.103	0.390	0.937	0.672
JPMorgan Chase	JPM	0.114	5.420	2.552	261.459	0.716	0.832	0.940
Wal-Mart	WMT	0.148	2.761	1.443	114.639	0.611	0.925	0.810
Nike	NKE	0.192	3.431	1.980	84.338	0.581	0.943	0.785
American Express	AXP	0.088	4.603	2.184	290.338	0.602	0.948	0.949
Intel	INTC	0.208	4.654	2.674	89.735	0.731	0.949	0.968
Travelers	TRV	0.098	3.579	1.637	273.579	0.646	0.933	0.915
Verizon	VZ	0.145	2.788	1.637	99.821	0.646	0.952	0.859
The Home Depot	HD	0.171	3.798	2.161	133.855	0.633	0.946	0.992
Cisco Systems	CSCO	0.234	5.120	2.742	96.212	0.715	0.939	0.942
UnitedHealth Group	UNH	0.222	4.145	2.304	169.815	0.616	0.920	0.846

# In-Sample Estimates

	AR	HAR	AR-IV	ARQ	HARQ	HARQ-F
$\beta_0$	0.4109 (0.1045)	0.1123 (0.0615)		0.0892 (0.0666)	-0.0098 (0.0617)	-0.0187 (0.0573)
$\beta_1$	0.6508 (0.1018)	0.2273 (0.1104)	0.9529 (0.0073)	<b>0.9830</b> (0.0782)	0.6021 (0.0851)	0.5725 (0.0775)
$\beta_2$		0.4903 (0.1352)			0.3586 (0.1284)	0.4368 (0.1755)
$\beta_3$		0.1864 (0.1100)			0.0976 (0.1052)	0.0509 (0.1447)
$\beta_{1Q}$				<b>-0.5139</b> (0.0708)	<b>-0.3602</b> (0.0637)	-0.3390 (0.0730)
$\beta_{2Q}$						-0.1406 (0.3301)
$\beta_{3Q}$						0.0856 (0.3416)
$R^2$	0.4235	<b>0.5224</b>	0.3323	<b>0.5263</b>	<b>0.5624</b>	0.5628
MSE	3.1049	2.5722	3.5964	2.5512	2.3570	2.3546
QLIKE	0.2111	0.1438	0.1586	0.1530	0.1358	0.1380
$\bar{R}^2$ Stocks	0.3975	0.4852	0.2935	0.4676	0.5090	0.5139
$\bar{MSE}$ Stocks	17.4559	14.9845	20.0886	15.2782	14.1702	14.0154
$\bar{QLIKE}$ Stocks	0.2095	0.1496	0.1759	0.1804	0.1470	0.1547

## Extended set of benchmark models

- HAR with Jumps (**HAR-J**) (Andersen, Bollerslev and Diebold, 2007):

$$RV_t = \beta_0 + \beta_1 RV_{t-1} + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \beta_J J_{t-1} + \epsilon_t$$

- Continuous HAR (**CHAR**) (Andersen, Bollerslev and Diebold, 2007):

$$RV_t = \beta_0 + \beta_1 BPV_{t-1} + \beta_2 BPV_{t-1|t-5} + \beta_3 BPV_{t-1|t-22} + \epsilon_t$$

- Semi-variance HAR (**SHAR**) (Patton and Sheppard, 2015):

$$RV_t = \beta_0 + \beta_1^+ RV_{t-1}^+ + \beta_1^- RV_{t-1}^- + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \epsilon_t$$

# Out-of-Sample Forecast Comparison

			AR	HAR	HAR-J	CHAR	SHAR	ARQ	HARQ	HARQ-F
S&P 500										
MSE	RW		0.9166	1.0000	0.9176	0.9583	0.8375	<b>0.8115</b>	0.8266	0.9750
	IW		1.2315	1.0000	0.9676	0.9707	0.9012	0.9587	<b>0.8944</b>	0.9312
QLIKE	RW		1.4559	1.0000	1.0062	1.0124	<b>0.9375</b>	0.9570	0.9464	0.9934
	IW		1.7216	1.0000	0.9716	0.9829	0.8718	1.1845	0.8809	<b>0.8686</b>
Individual Stocks										
MSE	RW	Avg	1.1505	1.0000	1.0151	1.0080	1.0083	0.9659	<b>0.9349</b>	1.0149
		Med	1.1730	1.0000	1.0115	1.0158	1.0020	0.9864	<b>0.9418</b>	1.0263
	IW	Avg	1.2130	1.0000	1.0040	1.0013	0.9947	1.0371	<b>0.9525</b>	1.0071
		Med	1.2161	1.0000	1.0028	1.0010	0.9968	1.0396	<b>0.9525</b>	0.9660
QLIKE	RW	Avg	1.4204	1.0000	1.0018	0.9999	0.9902	1.1498	<b>0.9902</b>	1.1516
		Med	1.4044	1.0000	0.9976	1.0025	0.9941	1.1781	<b>0.9916</b>	1.1051
	IW	Avg	1.5803	1.0000	0.9930	1.0148	0.9829	1.2024	<b>0.9487</b>	0.9843
		Med	1.5565	1.0000	0.9959	1.0163	0.9887	1.1732	<b>0.9550</b>	0.9630

# Weekly Forecast Horizon

			AR	HAR	HAR-J	CHAR	SHAR	ARQ	HARQ	HARQ-F	HARQ-h
S&P500											
MSE	RW		1.1450	1.0000	1.4030	0.9919	<b>0.9018</b>	1.0798	0.9475	1.2138	0.8884
	IW		1.3509	1.0000	1.1549	0.9673	<b>0.8365</b>	1.0861	0.9031	0.9171	0.9232
QLIKE	RW		1.5589	1.0000	1.3047	1.0417	0.9350	1.1892	<b>0.9159</b>	1.2529	0.9491
	IW		1.8801	1.0000	1.0898	0.9870	0.8735	1.3717	0.8537	<b>0.7540</b>	0.7996
Individual Stocks											
MSE	RW	Avg	1.2902	1.0000	1.0580	0.9960	0.9864	1.0985	0.9838	1.0234	<b>0.9765</b>
		Med	1.2859	1.0000	1.0504	0.9948	0.9904	1.1109	0.9806	1.0051	<b>0.9517</b>
	IW	Avg	1.4259	1.0000	1.0500	1.0003	0.9955	1.2126	0.9627	0.9601	<b>0.9477</b>
		Med	1.4322	1.0000	1.0435	1.0005	0.9922	1.2110	0.9596	0.9378	<b>0.9311</b>
QLIKE	RW	Aveg	1.6564	1.0000	1.1034	1.0124	0.9820	1.2111	<b>0.9309</b>	1.0665	0.9873
		Med	1.6554	1.0000	1.0980	1.0156	0.9827	1.2010	<b>0.9422</b>	1.0673	0.9869
	IW	Avg	1.9062	1.0000	1.0894	1.0279	0.9770	1.4147	<b>0.9066</b>	0.8529	0.8530
		Med	1.8762	1.0000	1.0721	1.0265	0.9781	1.4044	<b>0.9186</b>	0.8420	0.8579

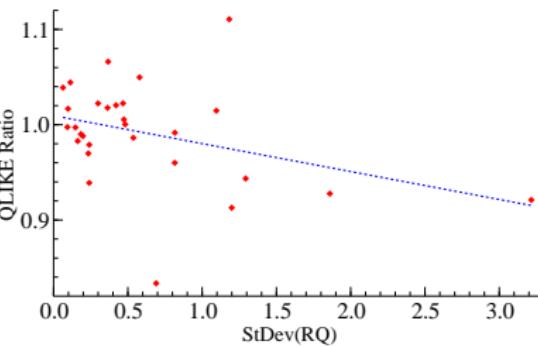
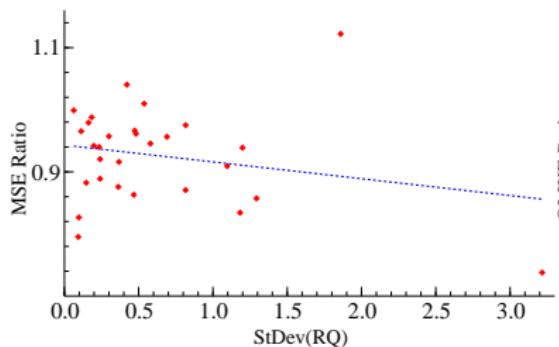
# Monthly Forecast Horizon

			AR	HAR	HAR-J	CHAR	SHAR	ARQ	HARQ	HARQ-F	HARQ-h
S&P500											
MSE	RW		1.1407	1.0000	0.9841	0.9642	<b>0.9558</b>	1.0964	1.0708	1.3485	1.2191
	IW		1.2411	1.0000	1.0312	1.0107	1.0119	1.1456	0.9667	<b>0.9339</b>	0.9832
QLIKE	RW		1.2455	1.0000	1.0552	0.9919	<b>0.9532</b>	1.0518	0.9808	1.1150	1.0450
	IW		1.4159	1.0000	1.0773	0.9937	0.9842	1.2144	0.9368	<b>0.8448</b>	0.8843
Individual Stocks											
MSE	RW	Avg	1.2246	1.0000	1.0173	1.0159	0.9924	1.0969	0.9953	1.0198	<b>0.9756</b>
		Med	1.2613	1.0000	1.0118	1.0105	0.9949	1.1005	0.9965	0.9963	<b>0.9619</b>
QLIKE	IW	Avg	1.4127	1.0000	1.0181	1.0123	0.9907	1.2366	0.9770	<b>0.9723</b>	0.9815
		Med	1.4052	1.0000	1.0172	1.0145	0.9927	1.2182	0.9692	<b>0.9480</b>	0.9705
MSE	RW	Avg	1.4125	1.0000	1.0385	1.0143	0.9909	1.1335	0.9485	0.9127	<b>0.8804</b>
		Med	1.4300	1.0000	1.0367	1.0125	0.9928	1.1228	0.9481	0.8778	<b>0.8635</b>
QLIKE	IW	Avg	1.6612	1.0000	1.0360	1.0257	0.9885	1.3519	0.9371	<b>0.8185</b>	0.8278
		Med	1.6294	1.0000	1.0224	1.0296	0.9912	1.3619	0.9442	<b>0.8245</b>	0.8442

# Persistence or Jumps

			AR	HAR	HAR-J	CHAR	SHAR	ARQ	HARQ	HARQ-F
<b>Bottom 95% <math>RQ_t</math></b>										
MSE	RW	Avg	1.2081	1.0000	0.9939	1.0044	0.9869	1.0324	<b>0.9557</b>	0.9928
		Med	1.1987	1.0000	0.9957	1.0034	0.9915	1.0459	<b>0.9693</b>	0.9802
	IW	Avg	1.2823	1.0000	0.9944	1.0053	0.9865	1.0814	<b>0.9633</b>	0.9581
		Med	1.2114	1.0000	0.9971	1.0067	0.9937	1.0675	<b>0.9697</b>	0.9684
QLIKE	RW	Avg	1.4379	1.0000	0.9962	1.0067	0.9888	1.1309	<b>0.9787</b>	1.1212
		Med	1.4399	1.0000	0.9958	1.0127	0.9934	1.1180	<b>0.9820</b>	1.0673
	IW	Avg	1.6204	1.0000	0.9979	1.0257	0.9787	1.1920	<b>0.9353</b>	0.9639
		Med	1.5941	1.0000	0.9995	1.0258	0.9833	1.1616	<b>0.9395</b>	0.9532
<b>Top 5% <math>RQ_t</math></b>										
MSE	RW	Avg	1.1426	1.0000	1.0228	1.0112	1.0163	0.9461	<b>0.9268</b>	1.0222
		Med	1.1591	1.0000	1.0212	1.0175	1.0073	0.9614	<b>0.9217</b>	1.0383
	IW	Avg	1.1933	1.0000	1.0053	0.9981	0.9983	1.0243	<b>0.9476</b>	1.0124
		Med	1.1984	1.0000	1.0052	1.0007	0.9979	1.0417	<b>0.9479</b>	0.9677
QLIKE	RW	Avg	1.3380	1.0000	1.0308	<b>0.9633</b>	1.0056	1.3161	1.0916	1.3535
		Med	1.3408	1.0000	0.9998	<b>0.9377</b>	1.0097	1.3052	1.0846	1.3250
	IW	Avg	1.3112	1.0000	0.9564	<b>0.9350</b>	1.0130	1.2864	1.0464	1.1301
		Med	1.3049	1.0000	0.9636	<b>0.9371</b>	1.0111	1.2186	1.0180	1.0045

# HARQ/HAR Loss Ratios



- Previous HARQ results based on simple **five-minute  $RV$** 
  - Ameliorates the effect of market microstructure “noise”
- Many alternative “robust” estimators allowing for the use of higher frequency data
  - Subsampled five-minute  $RV$  (**SS-RV**) (Aït-Sahalia, Mykland and Zhang, 2005)
  - Two-scale  $RV$  (**TS-RV**) (Zhang, Mykland and Aït-Sahalia, 2005)
  - Realized kernel  $RV$  (**RK**) (Barndorff-Nielsen, Hansen, Lunde and Shephard, 2008)
  - Pre-averaged  $RV$  (**PA-RV**) (Jacod, Li, Mykland, Podolskij and Vetter, 2009)
- We implement these alternative estimators using **one-minute** returns

- HAR based on alternative one-minute *RVs* versus HARQ based on simple five-minute *RV*:

		RV	SS-RV	TS-RV	RK	PA-RV
S&P 500						
MSE	RW	1.2574	1.0801	1.3472	1.3443	1.3521
	IW	1.1290	1.1882	1.2468	1.1769	1.1604
QLIKE	RW	1.0025	1.0149	1.1476	1.0493	1.0331
	IW	1.1487	1.1424	1.2637	1.4182	1.3608
Individual Stocks						
MSE	RW	Ave	1.0714	1.0523	1.1641	1.0446
		Med	1.0628	1.0430	1.1665	1.0604
QLIKE	IW	Ave	1.0531	1.0502	1.1319	1.0603
		Med	1.0499	1.0544	1.1206	1.0695
	RW	Ave	1.0100	1.0438	1.0890	1.0615
		Med	1.0064	1.0457	1.0923	1.0587
	IW	Ave	1.0552	1.0535	1.1297	1.1557
		Med	1.0471	1.0491	1.1240	1.1520

- HARQ versus HAR based on same  $RVs$ :

		RV	SS-RV	TS-RV	RK	PA-RV
S&P 500						
MSE	RW	0.7953	1.0059	0.8606	0.7873	0.7896
	IW	0.8857	0.8837	0.9749	0.8956	0.8952
QLIKE	RW	0.9975	1.0585	0.9776	0.9711	1.0504
	IW	0.8705	0.9195	0.9317	0.8971	0.9262
Individual Stocks						
MSE	RW	Ave	0.9333	0.9496	0.9547	1.0072
		Med	0.9409	0.9593	0.9521	1.0012
	IW	Ave	0.9496	0.9582	0.9723	0.9755
		Med	0.9525	0.9590	0.9730	0.9710
QLIKE	RW	Ave	0.9901	0.9462	0.9804	1.0874
		Med	0.9936	0.9600	0.9831	0.9973
	IW	Ave	0.9477	0.9474	0.9665	0.9492
		Med	0.9550	0.9447	0.9624	0.9431

- Previous HARQ results based on simple **five-minute  $RQ$** 
  - $I/Q$  is difficult to accurately estimate
- Many alternative  $I/Q$  estimators available
  - Tri-Power Quarticity (**TPQ**) (Barndorff-Nielsen and Shephard, 2006)
  - Median  $RQ$  (**MedRQ**) (Andersen, Dobrev and Schaumburg, 2012)
  - Truncated  $RQ$  (**TrRQ**) (Mancini, 2009)
  - Coarser sampled  $RQ$  ( **$RQ_{15min}$** ) (Bandi and Russell, 2008)
  - Bootstrapped variance of  $RV$  (**Bootstrap**) (Gonçalves and Meddahi, 2009)
- We implement the HARQ model with these alternative  $RQ$  estimators

- HARQ based on alternative *RQ* estimators versus HARQ based on five-minute *RQ*:

IQ-estimator		RQ	TPQ	MedRQ	TrRQ	$RQ_{15min}$	Bootstrap
S&P500							
MSE	RW	1.0000	1.0497	1.0254	1.0208	1.0590	<b>0.9925</b>
	IW	1.0000	1.1635	1.0328	<b>0.9948</b>	0.9805	0.9981
QLIKE	RW	1.0000	1.0933	1.1227	0.9971	1.0231	<b>0.9933</b>
	IW	1.0000	<b>0.9814</b>	1.0548	1.2060	1.0414	0.9998
Average and Median Ratio across stocks							
MSE	RW	Avg	1.0000	1.0403	1.0139	1.0531	1.0586
		Med	<b>1.0000</b>	1.0497	1.0201	1.0378	1.0238
QLIKE	IW	Avg	1.0000	1.0211	1.0191	1.0491	1.0229
		Med	1.0000	1.0220	1.0259	1.0558	1.0125
MSE	RW	Avg	1.0000	1.0040	1.0089	1.0541	1.0254
		Med	1.0000	0.9980	<b>0.9968</b>	1.0376	1.0015
QLIKE	IW	Avg	<b>1.0000</b>	1.0050	1.0047	1.0390	1.0014
		Med	<b>1.0000</b>	1.0040	1.0065	1.0303	0.9989

- The simple and easy-to-implement HARQ model relies on  $RQ^{1/2}$  to adjust for the time-varying attenuation bias:

$$RV_t = \beta_0 + \underbrace{(\beta_1 + \beta_{1Q} RQ_{t-1}^{1/2})}_{\beta_{1,t}} RV_{t-1} + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \epsilon_t$$

- AR(1) suggests using nonlinear function of  $RQ^{-1}$
  - Built-in robustness
  - Taylor series approximation
- 
- We implement the HARQ model with different functions of  $RQ$  in place of  $RQ^{1/2}$ 
    - $RQ, RQ^{-1/2}, RQ^{-1}, \log(RQ)$
    - Higher-order terms

- Different HARQ specifications versus HARQ based on  $RQ^{1/2}$ :

		$RQ_t$	$RQ_t^{1/2}$	$RQ_t^{-1/2}$	$RQ_t^{-1}$	$\log(RQ_t)$
S&P500						
MSE	RW	1.0037	<b>1.0000</b>	1.2123	1.2334	1.3313
	IW	1.0344	<b>1.0000</b>	1.1166	1.1357	1.0736
QLIKE	RW	<b>0.9484</b>	1.0000	1.0952	1.0950	1.8104
	IW	1.0222	<b>1.0000</b>	1.1327	1.3217	2.0107
Average and Median across stocks						
MSE	RW	Avg	1.0108	<b>1.0000</b>	1.0808	1.0931
		Med	1.0112	<b>1.0000</b>	1.0577	1.0664
QLIKE	IW	Avg	1.0189	<b>1.0000</b>	1.0495	1.0644
		Med	1.0198	<b>1.0000</b>	1.0403	1.0598
MSE	RW	Avg	<b>0.9973</b>	1.0000	1.0678	1.0814
		Med	<b>0.9847</b>	1.0000	1.0458	1.0579
QLIKE	IW	Avg	1.0263	<b>1.0000</b>	1.0961	1.1155
		Med	1.0241	<b>1.0000</b>	1.0778	1.0886

- All of the benchmark models may be similarly adjusted for measurement errors
  - HARQ-J:

$$\begin{aligned} RV_t = & \beta_0 + (\beta_1 + \beta_{1Q}\sqrt{RQ_{t-1}})RV_{t-1} \\ & + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \beta_J J_{t-1} + \epsilon_t \end{aligned}$$

- CHARQ:

$$\begin{aligned} RV_t = & \beta_0 + (\beta_1 + \beta_{1Q}\sqrt{TPQ_{t-1}})BPV_{t-1} \\ & + \beta_2 BPV_{t-1|t-5} + \beta_3 BPV_{t-1|t-22} + \epsilon_t \end{aligned}$$

- SHARQ:

$$\begin{aligned} RV_t = & \beta_0 + (\beta_1^+ + \beta_{1Q}^+\sqrt{RQ_{t-1}})RV_{t-1}^+ \\ & + (\beta_1^- + \beta_{1Q}^-\sqrt{RQ_{t-1}})RV_{t-1}^- \\ & + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + \epsilon_t. \end{aligned}$$

- HARQ-versions versus HAR-versions:

		HARQ	HARQ-J	CHARQ	SHARQ
S&P500					
MSE	RW	0.8266	0.9243	0.8951	1.4412
	IW	0.8944	0.9335	1.0609	1.1027
QLIKE	RW	1.0168	0.9653	1.0235	1.4576
	IW	0.8809	0.9015	0.8825	1.2849
Average and Median Ratio across stocks					
MSE	RW	Avg	0.9349	0.9397	0.9525
		Med	0.9418	0.9513	0.9539
	IW	Avg	0.9525	0.9666	0.9451
		Med	0.9525	0.9662	0.9548
QLIKE	RW	Avg	0.9902	0.9902	0.9879
		Med	0.9916	0.9952	0.9900
	IW	Avg	0.9487	0.9548	0.9306
		Med	0.9550	0.9594	0.9277

- We propose a class of realized-based volatility forecasting models that explicitly incorporate the **heteroskedasticity** of the measurement errors into the forecasts
  - Higher/lower weights on lagged *RVs* when estimated precisely/imprecisely
  - The **HARQ** model is particularly easy to estimate and implement and performs well empirically
- Same idea readily extends to other realized volatility based models and forecasting procedures
  - Currently working on multivariate vech-HARQ, HEAVY-Q and Realized GARCH-Q extensions
- Same idea may be applied to the forecasts of other economic time series subject to measurement errors
  - Currently working on surveys of professional forecasters

# Thank You!

