MTH 9875 The Volatility Surface: Fall 2015

Lecture 4: Efficient simulation of the Heston model

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Outline of lecture 4

- Heston variance simulation with full truncation
- The Ninomiya-Victoir scheme
  - Alfonsi's variance discretization
  - Full NV Heston discretization
- Variance reduction techniques
- Applications
  - The volatility smile
  - Local variance
  - The volatility surface

First download some code

In [1]:
```
download.file(url="http://mfe.baruch.cuny.edu/wp-content/uploads/2015/09/9875-4.zip", destfile="9875-4.zip")
unzip(zipfile="9875-4.zip")
source("BlackScholes.R")
source("Heston.R")
```

Heston parameters

In [2]:
```
paramsBCC <- list(lambda = 1.15,rho = -0.64,eta = 0.39,vbar = 0.04,v =
0.04)
paramsBCC1 <- list(lambda = 1.15,rho = -0.64,eta = .39/2,vbar = 0.04,v
= 0.04)
paramsBCC2 <- list(lambda = 1.15,rho = -0.64,eta = 0.39*2,vbar = 0.0
4,v = 0.04)
```

Recall from Lecture 3 that with both BCC and BCC2 parameters, zero is attainable.

Exact Heston implied volatility computations

To compute the bias of a simulation scheme, we need to know exact implied volatilities.

In [3]:
```
strikes <- c(0.8,1.0,1.2)
print(exactHestonVolsBCC <- sapply(strikes,function(K){impvolHeston(pa
ramsBCC)(log(K),1)}) )
print(exactHestonVolsBCC1 <- sapply(strikes,function(K){impvolHeston(p
aramsBCC1)(log(K),1)}) )
print(exactHestonVolsBCC2 <- sapply(strikes,function(K){impvolHeston(p
aramsBCC2)(log(K),1)}) )
```

```
[1] 0.2289957 0.1817281 0.1520478
[1] 0.2184855 0.1940710 0.1748623
[1] 0.2320480 0.1532666 0.1334544
```

Note how the skew increases as we increase η!

Code for Euler with partial truncation

Recall that this discretization reads:

$$v_{t+\Delta} = v_t - \lambda \left(v_t - \bar{v}\right) \Delta + \eta \sqrt{v_t^+} \sqrt{\Delta}\, Z.$$

In [4]:
```
evolveEulerP <- function(v,x,dt,Z,W,i){

        #Variance process
        v2 <- (v > 0) * v  # Take v2 = 0 if v<0, else v2=v
        vf <- v - lambda*(v-vbar)*dt +eta * sqrt(v2)*sqrt(dt)*W

        # Log-stock process
        x <- x  - (v+vf)/4*dt + sqrt(v2*dt) * Z
        # Impose martingale constraint
        x <- x - log(mean(exp(x)))
        v <- vf

        return(cbind(x,v))
}
```

Code for Euler with full truncation

Recall that this discretization reads:

$$v_{t+\Delta} = v_t - \lambda \left(v_t^+ - \bar{v}\right) \Delta + \eta \sqrt{v_t^+} \sqrt{\Delta}\, Z.$$

In [5]:
```
evolveEulerF <- function(v,x,dt,Z,W,i){

        #Variance process
        v2 <- (v > 0) * v  # Take v2 = 0 if v<0, else v2=v
        vf <- v - lambda*(v2-vbar)*dt +eta * sqrt(v2)*sqrt(dt)*W

        # Log-stock process
        x <- x  - (v+vf)/4*dt + sqrt(v2*dt) * Z
        # Impose martingale constraint
        x <- x - log(mean(exp(x)))
        v <- vf

        return(cbind(x,v))
}
```

Heston code that uses the above time discretization

Note that the code also does Richardson extrapolation.

In [6]:
```
is.even <- function(j){as.logical((j+1) %% 2)} # A little function n
eeded later

HestonMC <- function(params){

    res <- function(S0, T, AK, N, m, evolve,exactVols=NULL)
    {

    lambda <<- params$lambda
    rho <<- params$rho
    eta <<- params$eta
    vbar <<- params$vbar
    v0 <<- params$v

        phi <<- sqrt(1-rho^2)

    n <- m*2  #n is number of timesteps = 2*m so we can use Richards
on extrapolation
    sqrt2 <- sqrt(2)
    rho2m1 <- sqrt(1-rho*rho)

    negCount <- 0

    # We use a vertical array, one element per M.C. path
    x <- rep(0,N); v <- rep(1,N)*v0
    xm <- x; vm <- v
    W1m <- rep(0,N); W2m <- rep(0,N)

    # Loop for bias computation (N small, n big)
    for (i in 1:n)
    {
        # Two sets of correlated normal random vars.

        W1 <- rnorm(N)
        W2 <- rnorm(N)
        W1 <- W1 - mean(W1);  W1 <- W1/sd(W1)
        W2 <- W2 - mean(W2);  W2 <- W2/sd(W2)
        # Now W1 and W2 are forced to have mean=0 and sd=1

        W2p <- W2 - cor(W1,W2)*W1  # Eliminate actual correlation
        W2p <- W2p - mean(W2p);  W2 <- W2p/sd(W2p)
        W2 <- rho*W1 + rho2m1*W2
        # Now W1 and W2 have mean=0, sd=1 and correlation rho

        # Add code for subgrid
        W1m <- W1m + W1/sqrt2;  W2m <- W2m + W2/sqrt2  # N(0,1) rv's
for subgrid

        if (is.even(i)) {
            #print(c(i,mean(W1m),mean(W2m),sd(W1m),sd(W2m),cor(W1m,W
2m)))
            resm <- evolve(vm,xm,T/m,W1m,W2m,i/2)
```

```
            xm <- resm[,1]
            vm <- resm[,2]
            W1m <- rep(0,N);  W2m <- rep(0,N)
        }

        res <- evolve(v,x,T/n,W1,W2,i)
        x <- res[,1]
        v <- res[,2]
        negCount <- negCount +mean(v<0)/n  #Probability of negative
variance per path per timestep

  }

    S <- S0*exp(x)
    Sm <- S0*exp(xm)

    # Now we have three vectors of final stock prices

    M <- length(AK)
    AV <- numeric(M); AVdev <- numeric(M)
    BSV <- numeric(M); BSVH <- numeric(M);  BSVL <- numeric(M)
    iv2SD <- numeric(M);  bias <- numeric(M)
    AVm <- numeric(M);  AVmdev <- numeric(M)
    BSVm <- numeric(M);  BSVHm <- numeric(M);  BSVLm <- numeric(M)
    iv2SDm <- numeric(M)
    AV1 <- numeric(M);  AV1dev <- numeric(M)
    BSV1 <- numeric(M); BSVH1 <- numeric(M); BSVL1 <- numeric(M)
    iv2SDrom <- numeric(M); biasRom <- numeric(M)

  # Evaluate mean call value for each path
  for (i in 1:M)
  {
    # 2*m timesteps
    K <- AK[i]
    V <- (S>K)*(S - K)  # Boundary condition for European call
    AV[i] <- mean(V)
    AVdev[i] <- sqrt(var(V)/length(V))

    BSV[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i])
    BSVL[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] - AVdev[i])
    BSVH[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] + AVdev[i])
    iv2SD[i] <- (BSVH[i]-BSVL[i])

    # m timesteps
    Vm <- (Sm>K)*(Sm - K)  # Boundary condition for European call
    AVm[i] <- mean(Vm)
    AVmdev[i] <- sd(Vm) / sqrt(N)
    BSVm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i])
    BSVLm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] - AVmdev[i])
    BSVHm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] + AVmdev[i])
    iv2SDm[i] <- (BSVH[i]-BSVL[i])

    # Romberg estimates
```

```
    V1 <- 2*V - Vm
    AV1[i] <- mean(V1)
    AV1dev[i] <- sd(V1) / sqrt(N)
    BSV1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i])
    BSVL1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] - AV1dev[i])
    BSVH1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] + AV1dev[i])
    iv2SDrom[i] <- (BSVH1[i]-BSVL1[i])

    if(!is.null(exactVols)) {bias <- BSV-exactVols}
    if(!is.null(exactVols)) {biasRom <- BSV1-exactVols}
  }

  l.AK <- length(AK)
  data.out <- data.frame(AK,rep(N,l.AK),rep(2*m,l.AK),BSV,bias,iv2S
D,BSVm,BSV1,biasRom,iv2SDrom)
  names(data.out) <- c("Strikes","Paths","Steps","ivol","bias","twoS
d","ivolm", "ivolRichardson", "biasRichardson","twoSdRichardson")
  return(data.out)


}
return(res)
}
```

Here's an example of a function call:

In [7]:
```
HestonMC(paramsBCC)(S0=1, T=1, strikes, N=100000, m=4, evolve=evolveEu
lerF, exactVols=exactHestonVolsBCC)
```

Out[7]:

	Strikes	Paths	Steps	ivol	bias	twoSd	ivolm
1	0.8	1e+05	8	0.2310575	0.002061791	0.004443198	0.2337710
2	1.0	1e+05	8	0.1855852	0.003857069	0.001606880	0.1931710
3	1.2	1e+05	8	0.1564881	0.004440381	0.001159100	0.1667388

	ivolRichardson	biasRichardson	twoSdRichardson
1	0.2283144	-0.000681290	0.005044522
2	0.1780021	-0.003726078	0.001902873
3	0.1452307	-0.006817066	0.001614098

Convergence with BCC parameters

In [8]:
```
load("mc.convergence.rData")
```

In [9]:
```
tmp <- resF.BCC
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="purple",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="purple",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resP.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="red",ylab="Implied volat
ility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Yea
rs)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="red",lty=2)
```

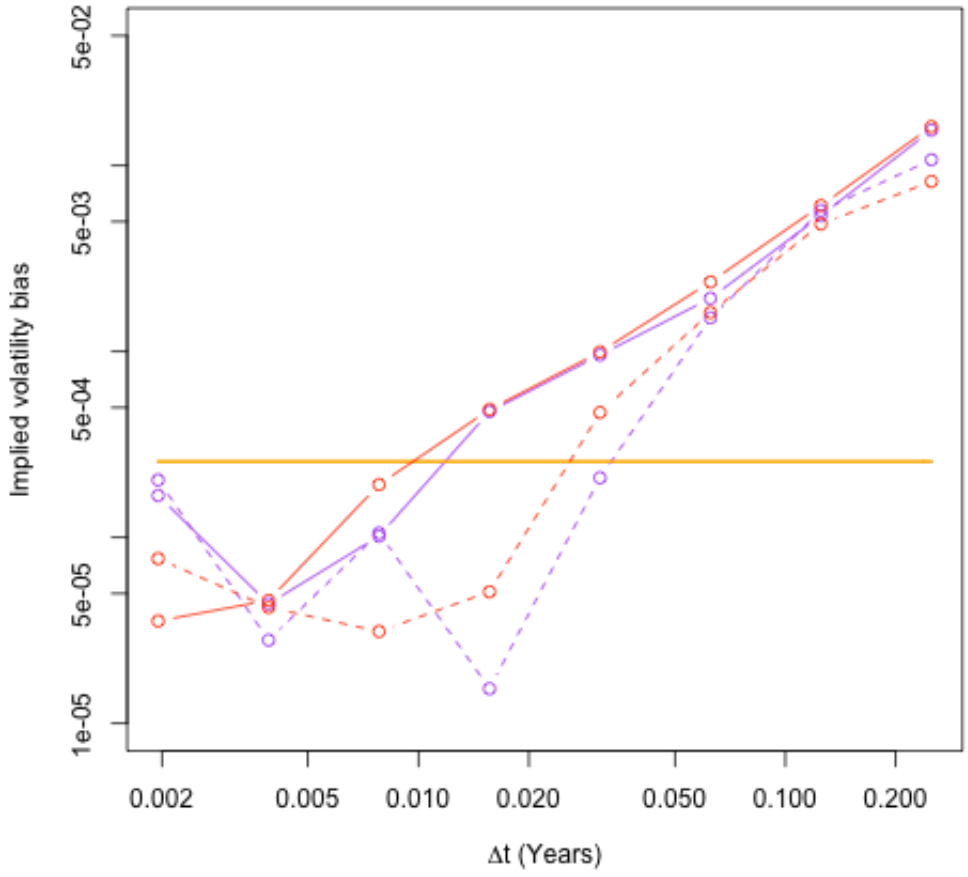

Figure 1: One year option, $K = 1.2$ with BCC parameters. Euler with partial truncation in red; full truncation in purple; dashed lines are from Richardson extrapolation.

- The difference between partial and full truncation seems to be minimal; full truncation wins by a hair.

Convergence with BCC2 parameters

In [10]:
```
tmp <- resF.BCC2
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="purple",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="purple",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resP.BCC2
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="red",ylab="Implied volat
ility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Yea
rs)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="red",lty=2)
```

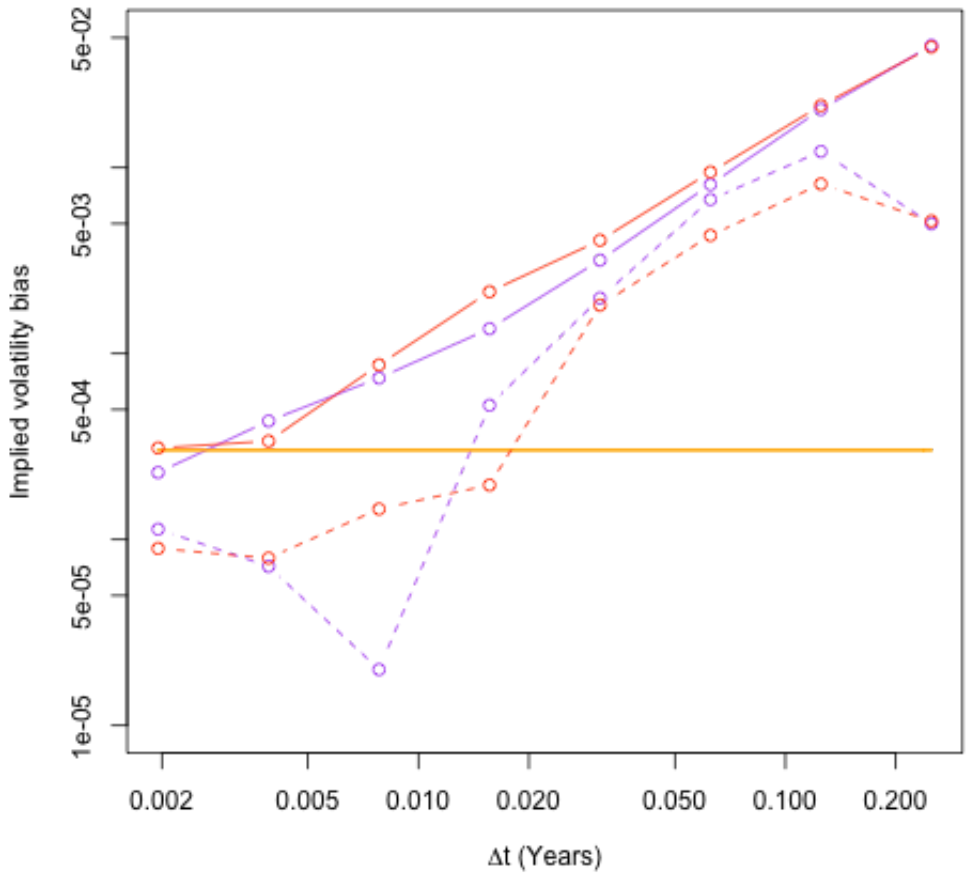

Figure 2: One year option, $K = 1.2$ with BCC2 parameters. Euler with partial truncation in red; full truncation in purple; dashed lines are from Richardson extrapolation.

- Again, full truncation wins by a hair.

Formal solution of the Heston SDE

We write the Heston SDE in the form

$$\begin{aligned} d(\log S) &= -\frac{v}{2}\,dt + \sqrt{v}\,\left\{\rho\,dW_t + \sqrt{1-\rho^2}\,dW_t^{\perp}\right\} \\ dv &= -\lambda(v-\bar{v})\,dt + \eta\sqrt{v}\,dW_t \end{aligned}$$

The exact solution may then be written as

(1)

$$\begin{aligned} S_t &= S_0\,\exp\left\{-\frac{1}{2}\int_0^t v_s\,ds + \rho\int_0^t \sqrt{v_s}\,dW_s + \sqrt{1-\rho^2}\int_0^t \sqrt{v_s}\,dW_s^{\perp}\right\} \\ v_t &= v_0 + \lambda\,\bar{v}\,t - \lambda\int_0^t v_s\,ds + \eta\int_0^t \sqrt{v_s}\,dW_s \end{aligned}$$

with $\mathbb{E}[dW_s\,dW_s^{\perp}] = 0$.

Andersen's simulation procedure

- [Andersen][2] proposes to simulate processes like the square-root variance process by sampling from a distribution that is similar to the true distribution but not the same.
  - This approximate distribution should have at least the same mean and variance as the true distribution.
  - More generally, this distribution should have a similar shape.

- Applying his approach to simulating the Heston process, we would have to at least find the means and variances of $\int_0^t \sqrt{v_s}\,dW_s$, $\int_0^t v_s\,ds$, v_t and v_0.
  - This can only be done when the mean and variance are computable.
  - These moments are computable in the case of the Heston model.

- Again, we want to focus on generic techniques.

Cross terms

- We have discretized the stock and variance parts of the Heston SDE to $\mathcal{O}(\Delta)$ separately.
  - In principle, we pick up higher order cross terms too.
  - However, the conditions for higher order schemes such as Milstein are not met in the Heston model so some say there is little advantage in getting more complicated.

- Andersen disagrees.
  - So far, we have discretized $x = \log S$ as

    (2)
    $$x_{t+\Delta} = x_t - \frac{1}{2}\left(v_t + v_{t+\Delta}\right)\Delta + \sqrt{v_t}\,\sqrt{\Delta}\,Z$$
    with $\mathbb{E}[W\,Z] = \rho$.
  - He observes that if there is a significant probability of a negative v, the actual correlation between Δv and Δx will not be ρ because v has been truncated.

Leaking correlation

Quote from [Andersen][2]

> If one were to "insist on using (2), at practical levels of Δ, one would experience a strong tendency for the Monte Carlo simulation to generate too feeble effective correlation and, consequently, paths of x with poor distribution tails. In call option pricing terms, this would manifest itself in an overall poor ability to price options with strikes away from at-the-money."

Andersen's solution

Noting that

$$\eta \sqrt{v_t}\, \sqrt{\Delta}\, W = v_{t+\Delta} - v_t + \lambda\left(v_t - \bar{v}\right)\Delta,$$

and motivated by the exact formal expression (1), Andersen suggests the following x-discretization instead:

(3)

$$\begin{aligned} x_{t+\Delta} &= x_t + \left(\frac{\rho}{\eta} - \frac{1}{2}\right)\left(v_t + v_{t+\Delta}\right)\Delta + \frac{\rho}{\eta}\left(v_{t+\Delta} - v_t + \lambda\left(v_t - \bar{v}\right)\Delta\right) \\ &\quad + \sqrt{1-\rho^2}\, \sqrt{\frac{1}{2}\left(v_t + v_{t+\Delta}\right)}\, \sqrt{\Delta}\, W^{\perp} \end{aligned}$$

where $W^{\perp}$ is orthogonal to W (from the variance process).

- Let's check to see if (3) really does better than (2)!

Code for Andersen discretization

First the `EulerF` timestep with Andersen x-discretization:

In [11]:
```
evolveEulerFAndersen <- function(v,x,dt,Z,W,i){

        #Variance process
        v2 <- (v > 0) * v  # Take v2 = 0 if v<0, else v2=v
        vf <-  v - lambda*(v2 - vbar)*dt +eta * sqrt(v2)*sqrt(dt)*W

        # Log-stock process (Andersen equation (33))
        vvf <- (v+vf > 0) * (v+vf)
        dw <- vvf/2*dt
        x <- x  - dw/2 + rho2m1*sqrt(dw)*Z +
            rho/eta*(lambda*dw + vf-v -lambda*vbar*dt)
        # Impose martingale constraint
        x <- x - log(mean(exp(x)))
        v <- vf
        return(cbind(x,v))
}
```

This new x-discretizations needs a new Monte Carlo routine:

In [12]:
```
HestonMCAndersen <- function(params){

    res <- function(S0, T, AK, N, m, evolve,exactVols=NULL)
    {

    lambda <<- params$lambda
    rho <<- params$rho
    eta <<- params$eta
    vbar <<- params$vbar
    v0 <<- params$v

    n <- m*2  #n is number of timesteps = 2*m so we can use Romberg
extrapolation
    sqrt2 <- sqrt(2)
    rho2m1 <<- sqrt(1-rho*rho)

    negCount <- 0

    # We use a vertical array, one element per M.C. path
    x <- rep(0,N);  v <- rep(1,N)*v0
    xm <- x;  vm <- v
    W1m <- rep(0,N);  W2m <- rep(0,N)

    # Loop for bias computation (N small, n big)
    for (i in 1:n)
    {
        # Two sets of correlated normal random vars.

        W1 <- rnorm(N)
        W2 <- rnorm(N)
        W1 <- W1 - mean(W1);  W1 <- W1/sd(W1)
        W2 <- W2 - mean(W2);  W2 <- W2/sd(W2)
        # Now W1 and W2 are forced to have mean=0 and sd=1

        W2p <- W2 - cor(W1,W2)*W1  # Eliminate actual correlation
        W2p <- W2p - mean(W2p);  W2 <- W2p/sd(W2p)
        # Now W1 and W2 have mean=0, sd=1 and correlation=0

        # Add code for subgrid
        W1m <- W1m + W1/sqrt2;  W2m <- W2m + W2/sqrt2  # N(0,1) rv's
for subgrid

        if (is.even(i)) {
            resm <- evolve(vm,xm,T/m,W1m,W2m,i/2)
            xm <- resm[,1]
            vm <- resm[,2]
            W1m <- rep(0,N);  W2m <- rep(0,N)
        }

        res <- evolve(v,x,T/n,W1,W2,i)
        x <- res[,1]
        v <- res[,2]
```

```
        negCount <- negCount +mean(v<0)/n  #Probability of negative
variance per path per timestep

  }

    S <- S0*exp(x)
    Sm <- S0*exp(xm)

    # Now we have three vectors of final stock prices

    M <- length(AK)
    AV <- numeric(M);  AVdev <- numeric(M)
    BSV <- numeric(M) ; BSVH <- numeric(M);  BSVL <- numeric(M)
    iv2SD <- numeric(M);  bias <- numeric(M)
    AVm <- numeric(M);  AVmdev <- numeric(M)
    BSVm <- numeric(M);  BSVHm <- numeric(M);  BSVLm <- numeric(M)
    iv2SDm <- numeric(M)
    AV1 <- numeric(M);  AV1dev <- numeric(M)
    BSV1 <- numeric(M);  BSVH1 <- numeric(M);  BSVL1 <- numeric(M)
    iv2SDrom <- numeric(M); biasRom <- numeric(M)

  # Evaluate mean call value for each path
  for (i in 1:M)
  {
    # 2*m timesteps
    K <- AK[i]
    V <- (S>K)*(S - K)  # Boundary condition for European call
    AV[i] <- mean(V)
    AVdev[i] <- sqrt(var(V)/length(V))

    BSV[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i])
    BSVL[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] - AVdev[i])
    BSVH[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] + AVdev[i])
    iv2SD[i] <- (BSVH[i]-BSVL[i])

    # m timesteps
    Vm <- (Sm>K)*(Sm - K)  # Boundary condition for European call
    AVm[i] <- mean(Vm)
    AVmdev[i] <- sd(Vm) / sqrt(N)
    BSVm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i])
    BSVLm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] - AVmdev[i])
    BSVHm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] + AVmdev[i])
    iv2SDm[i] <- (BSVH[i]-BSVL[i])

    # Romberg estimates
    V1 <- 2*V - Vm
    AV1[i] <- mean(V1)
    AV1dev[i] <- sd(V1) / sqrt(N)
    BSV1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i])
    BSVL1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] - AV1dev[i])
    BSVH1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] + AV1dev[i])
    iv2SDrom[i] <- (BSVH1[i]-BSVL1[i])
```

```
    if(!is.null(exactVols)) {bias <- BSV-exactVols}
    if(!is.null(exactVols)) {biasRom <- BSV1-exactVols}
  }

  l.AK <- length(AK)
  data.out <- data.frame(AK,rep(N,l.AK),rep(2*m,l.AK),BSV,bias,iv2S
D,BSVm,BSV1,biasRom,iv2SDrom)
  names(data.out) <- c("Strikes","Paths","Steps","ivol","bias","twoS
d","ivolm", "ivolRichardson", "biasRichardson","twoSdRichardson")
  return(data.out)

}
return(res)
}
```

Example of function call

In [13]:
```
HestonMCAndersen(paramsBCC)(S0=1, T=1, strikes, N=100000, m=16, evolv
e=evolveEulerFAndersen, exactVols=exactHestonVolsBCC)
```

Out[13]:

	Strikes	Paths	Steps	ivol	bias	twoSd	ivolm
1	0.8	1e+05	32	0.2304248	1.429107e-03	0.004372534	0.2322376
2	1.0	1e+05	32	0.1826494	9.212416e-04	0.001563084	0.1838195
3	1.2	1e+05	32	0.1520328	-1.491615e-05	0.001139029	0.1521258

	ivolRichardson	biasRichardson	twoSdRichardson
1	0.2285988	-0.0003969365	0.004584510
2	0.1814793	-0.0002488027	0.001653490
3	0.1519398	-0.0001079627	0.001215423

Convergence with BCC parameters

In [14]:
```
tmp <- resF.BCC
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="purple",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="purple",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resFAndersen.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="green4",ylab="Implied vo
latility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, "
(Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="green4",lt
y=2)
```

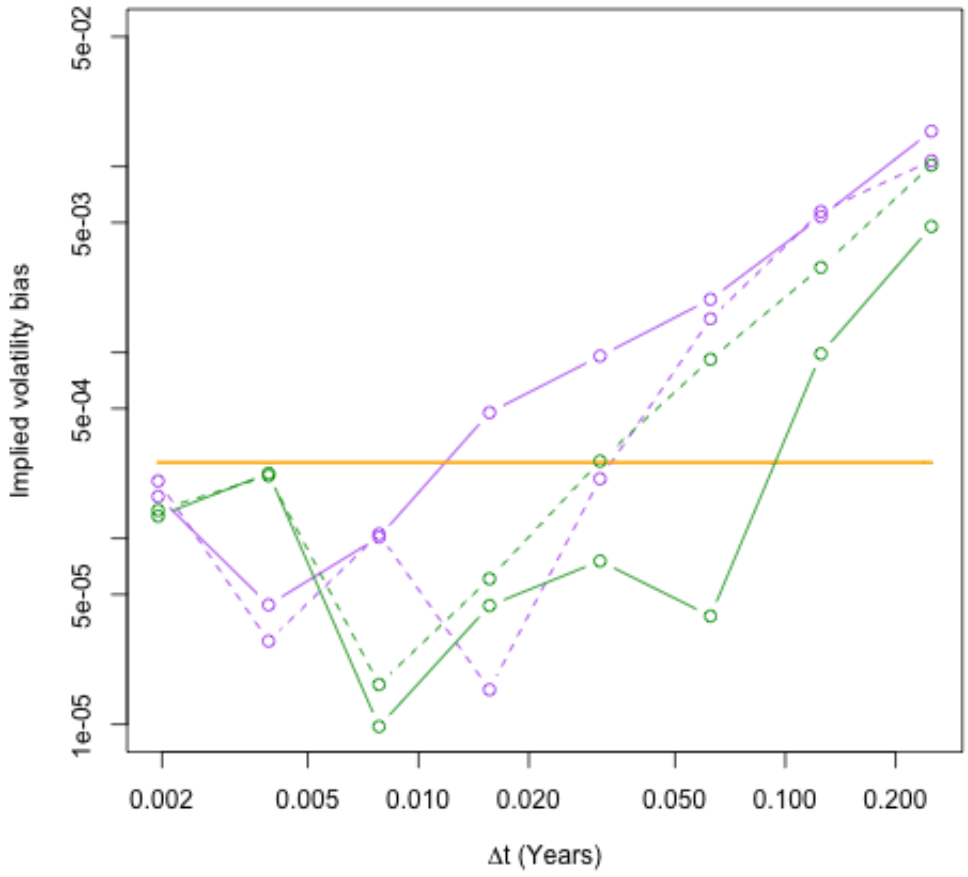

Figure 3: One year option, $K = 1.2$ with BCC parameters. Euler with full truncation in purple; with Andersen x-discretization in green; dashed lines are from Richardson extrapolation.

- Andersen's x discretization seems to do much better!

Convergence with BCC2 parameters

In [15]:
```
tmp <- resF.BCC2
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="purple",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="purple",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resFAndersen.BCC2
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="green4",ylab="Implied vo
latility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, "
(Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="green4",lt
y=2)
```

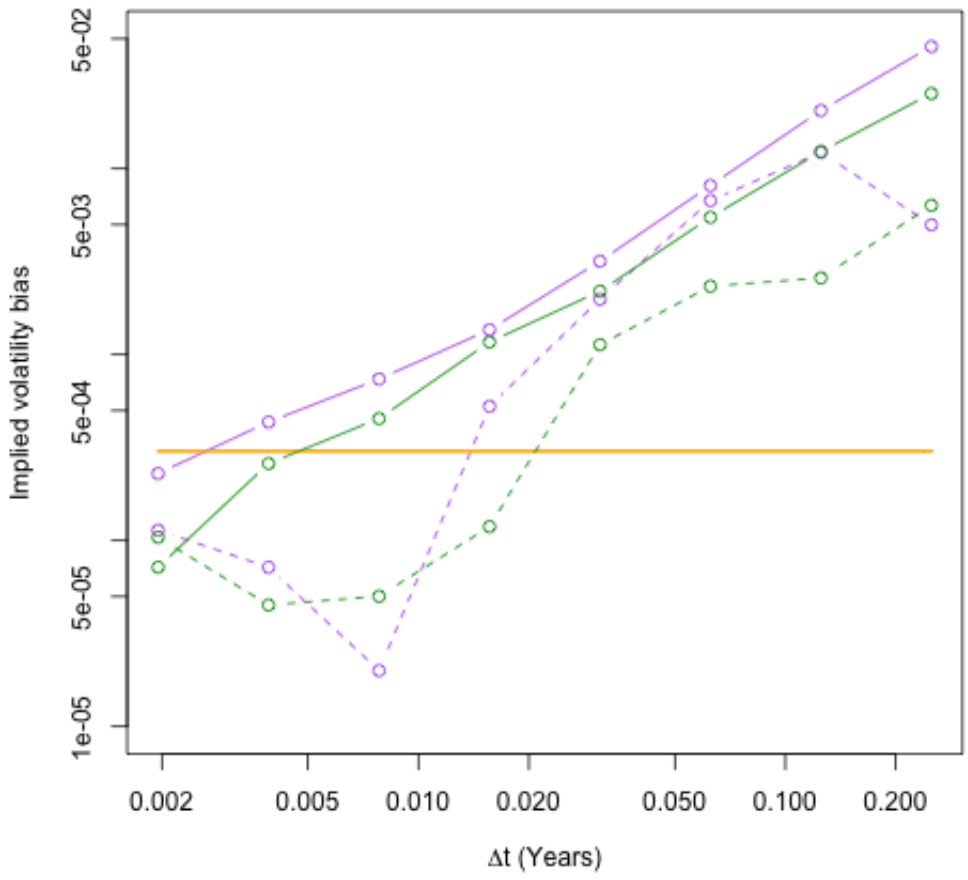

Figure 4: Euler with full truncation in purple; with Andersen x-discretization in green; dashed lines are with Richardson extrapolation ($K = 1.2$; $T = 1$)

- Andersen's discretization is better, and Richardson extrapolation improves it.

The Alfonsi Heston scheme

[Alfonsi (2010)][1] implements the following scheme for variance:

(4)

$$v_{t+\Delta} = e^{-\lambda\,\Delta/2}\left(\sqrt{v_t\,e^{-\lambda\,\Delta/2} + \left[\lambda\,\bar{v} - \frac{\eta^2}{4}\right]\,\psi\left(\frac{\Delta}{2}\right)} + \frac{\eta}{2}\sqrt{\Delta}\,Z\right)^2 + \left[\lambda\,\bar{v} - \frac{\eta^2}{4}\right]\,\psi\left(\frac{\Delta}{2}\right)$$

with $Z \sim N(0,1)$ and as before,

$$\psi(x) := \frac{1 - e^{-\lambda x}}{\lambda}$$

Note in particular that $v_{t+\Delta} > 0$ if $4\,\lambda\,\bar{v} > \eta^2$. So the discretized variance process cannot hit zero with BCC or BCC1 parameters.

Alfonsi (2010) code

In [16]:
```
evolveAlfonsi <- function(v,x,dt,W1,W2,L=NULL){

        eldt2 <- exp(-lambda*dt/2);

        #Variance process
        vbarp <- vbar - eta^2/(4*lambda);
        psi <- (1-eldt2)/lambda;
        v1 <- v*eldt2 + lambda*vbarp*psi;
        v2 <- (v1 > 0) * v1; # Take v2 = 0 if v1<0, else v2=v1
        par <- sqrt(v2) + eta/2*sqrt(dt)*W2;
        vf <- eldt2*par*par + lambda*vbarp*psi;

        # Log-stock process (Andersen equation (33))
        vvf <- (v+vf > 0) * (v+vf);
        dw <- vvf/2*dt;
        x <- x  - dw/2 + rho2m1*sqrt(dw)*W1 +
            rho/eta*(lambda*dw + vf-v -lambda*vbar*dt) ;
        # Impose martingale constraint
        x <- x - log(mean(exp(x)));
        v <- vf;
        return(cbind(x,v));
}
```

Here's Monte Carlo code that uses the above time step:

In [17]:
```
HestonMC2 <- function(params){

    is.even <- function(j){as.logical((j+1) %% 2)}

    res <- function(S0, T, AK, N, m, evolve,exactVols=NULL)
    {

    lambda <<- params$lambda;
    rho <<- params$rho;
    eta <<- params$eta;
    vbar <<- params$vbar;
    v0 <<- params$v;

    n <- m*2; #n is number of timesteps = 2*m so we can use Romberg ex
trapolation
    sqrt2 <- sqrt(2);
    rho2m1 <<- sqrt(1-rho*rho);
    vbarp <<- vbar - eta^2/(4*lambda);

    negCount <- 0;

    # We use a vertical array, one element per M.C. path
    x <- rep(0,N); v <- rep(1,N)*v0;
    xm <- x; vm <- v;
    W1m <- rep(0,N); W2m <- rep(0,N);

    # Loop for bias computation (N small, n big)
    for (i in 1:n)
    {
        # Two sets of correlated normal random vars.

        W1 <- rnorm(N);
        W2 <- rnorm(N);
        W1 <- W1 - mean(W1); W1 <- W1/sd(W1);
        W2 <- W2 - mean(W2); W2 <- W2/sd(W2);
        # Now W1 and W2 are forced to have mean=0 and sd=1

        W2p <- W2 - cor(W1,W2)*W1; # Eliminate actual correlation
        W2p <- W2p - mean(W2p); W2 <- W2p/sd(W2p);
        # Now W1 and W2 have mean=0, sd=1 and correlation=0

        L <- rbinom(N, size=1, prob=1/2); # Bernoulli rv for NV step

        # Add code for subgrid
        W1m <- W1m + W1/sqrt2; W2m <- W2m + W2/sqrt2; # N(0,1) rv's fo
r subgrid

        if (is.even(i)) {
            #print(c(i,mean(W1m),mean(W2m),sd(W1m),sd(W2m),cor(W1m,W2
m)));
            resm <- evolve(vm,xm,T/m,W1m,W2m,L);
            xm <- resm[,1];
```

```
            vm <- resm[,2];
            W1m <- rep(0,N); W2m <- rep(0,N);
        }

        res <- evolve(v,x,T/n,W1,W2,L);
        x <- res[,1];
        v <- res[,2];
        negCount <- negCount +mean(v<0)/n; #Probability of negative va
riance per path per timestep

  }

    S <- S0*exp(x);
    Sm <- S0*exp(xm);

    # Now we have three vectors of final stock prices

    M <- length(AK);
    AV <- numeric(M); AVdev <- numeric(M);
    BSV <- numeric(M); BSVH <- numeric(M); BSVL <- numeric(M);
    iv2SD <- numeric(M); bias <- numeric(M);
    AVm <- numeric(M); AVmdev <- numeric(M);
    BSVm <- numeric(M); BSVHm <- numeric(M); BSVLm <- numeric(M);
    iv2SDm <- numeric(M);
    AV1 <- numeric(M); AV1dev <- numeric(M);
    BSV1 <- numeric(M); BSVH1 <- numeric(M); BSVL1 <- numeric(M);
    iv2SDrom <- numeric(M);biasRom <- numeric(M);

  # Evaluate mean call value for each path
  for (i in 1:M)
  {
    # 2*m timesteps
    K <- AK[i];
    V <- (S>K)*(S - K); # Boundary condition for European call
    AV[i] <- mean(V);
    AVdev[i] <- sqrt(var(V)/length(V));

    BSV[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i]);
    BSVL[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] - AVdev[i]);
    BSVH[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] + AVdev[i]);
    iv2SD[i] <- (BSVH[i]-BSVL[i]);

    # m timesteps
    Vm <- (Sm>K)*(Sm - K); # Boundary condition for European call
    AVm[i] <- mean(Vm);
    AVmdev[i] <- sd(Vm) / sqrt(N);
    BSVm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i]);
    BSVLm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] - AVmdev[i]);
    BSVHm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] + AVmdev[i]);
    iv2SDm[i] <- (BSVH[i]-BSVL[i]);

    # Richardson extrapolation estimates
    V1 <- 2*V - Vm;
```

```
    AV1[i] <- mean(V1);
    AV1dev[i] <- sd(V1) / sqrt(N);
    BSV1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i]);
    BSVL1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] - AV1dev[i]);
    BSVH1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] + AV1dev[i]);
    iv2SDrom[i] <- (BSVH1[i]-BSVL1[i]);

    if(!is.null(exactVols)) {bias <- BSV-exactVols};
    if(!is.null(exactVols)) {biasRom <- BSV1-exactVols};
  }


  l.AK <- length(AK)
  data.out <- data.frame(AK,rep(N,l.AK),rep(2*m,l.AK),BSV,bias,iv2SD,B
SVm,BSV1,biasRom,iv2SDrom)
  names(data.out) <- c("Strikes","Paths","Steps","ivol","bias","twoS
d","ivolm", "ivolRichardson", "biasRichardson","twoSdRichardson")
  return(data.out)


}
return(res)
}
```

Here's an example of how to call the code:

In [18]:
```
HestonMC2(paramsBCC)(S0=1, T=1, AK=strikes, N=100000, m=4, evolve=evol
veAlfonsi, exactVols=exactHestonVolsBCC)
```

Out[18]:

	Strikes	Paths	Steps	ivol	bias	twoSd	ivolm
1	0.8	1e+05	8	0.2290701	7.433206e-05	0.004393698	0.2286915
2	1.0	1e+05	8	0.1818473	1.191834e-04	0.001567430	0.1815342
3	1.2	1e+05	8	0.1528003	7.525073e-04	0.001132833	0.1531273

	ivolRichardson	biasRichardson	twoSdRichardson
1	0.2294481	0.0004523493	0.004521863
2	0.1821605	0.0004323231	0.001638616
3	0.1524722	0.0004244599	0.001219249

Convergence of the Alfonsi scheme with BCC parameters

In [19]:
```
tmp <- resFAndersen.BCC
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="green4",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="green4",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resAlfonsi.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="brown",ylab="Implied vol
atility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Y
ears)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="brown",lty=2)
```

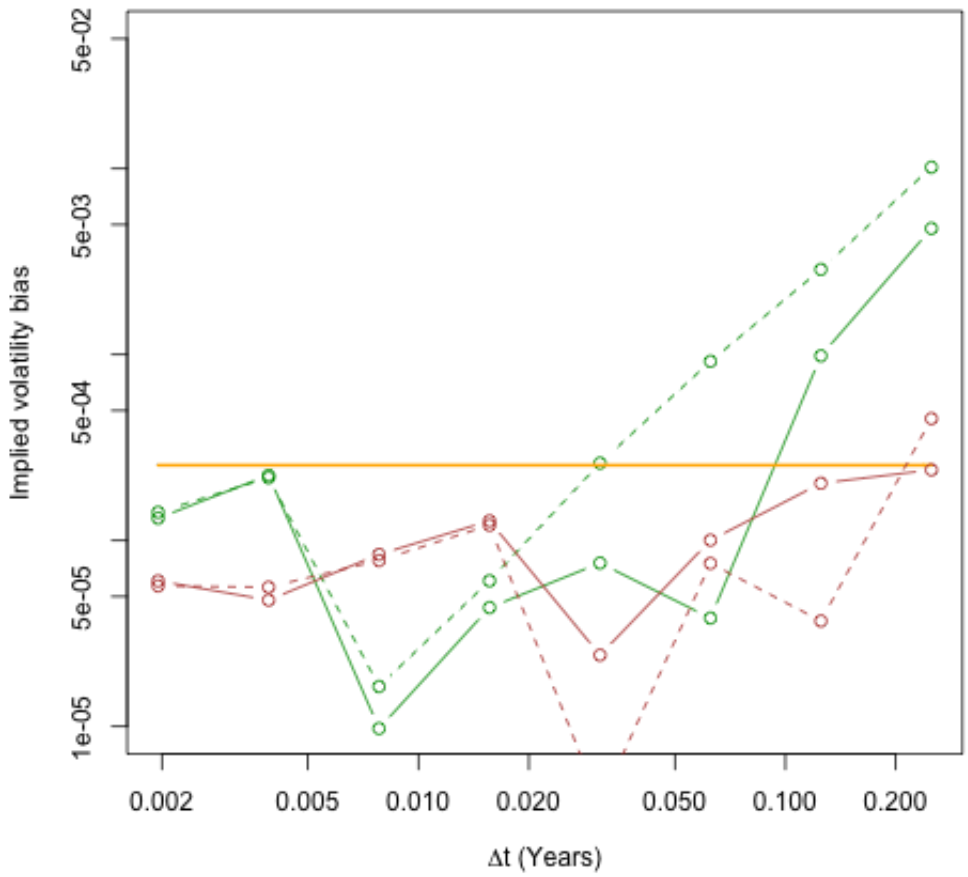

Figure 5: Euler with full truncation and Andersen x-discretization in green; Alfonsi in brown; dashed lines are with Richardson extrapolation ($T = 1$, $K = 1.2$)

Convergence of the Alfonsi scheme with BCC2 parameters

In [20]:
```
tmp <- resFAndersen.BCC2
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="green4",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="green4",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resAlfonsi.BCC2
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="brown",ylab="Implied vol
atility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Y
ears)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="brown",lty=2)
```

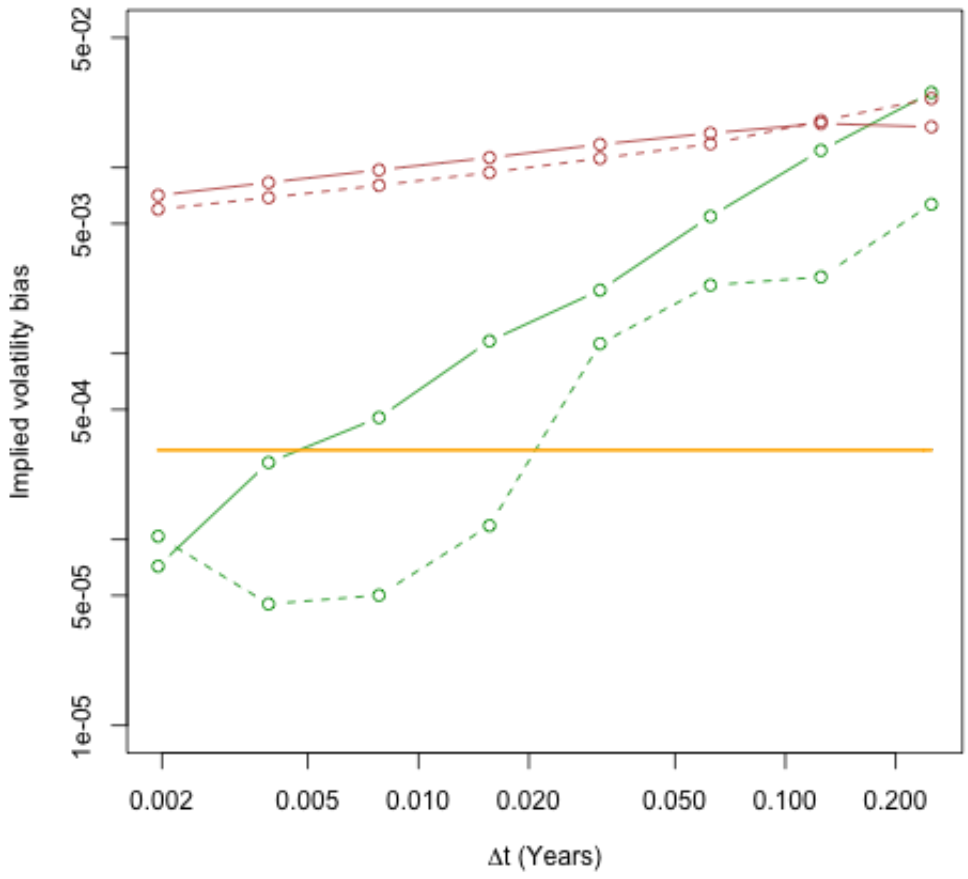

Figure 6: Euler with full truncation and Andersen x-discretization in green; Alfonsi in brown; dashed lines are with Richardson extrapolation ($T = 1$, $K = 1.2$)

- Now Alfonsi is underperforming.

Alfonsi code with full truncation

In [21]:
```
evolveAlfonsiF <- function(v,x,dt,W1,W2,L=NULL){

        eldt2 <- exp(-lambda*dt/2);

        #Variance process
        vbarp <- vbar - eta^2/(4*lambda);
        psi <- (1-eldt2)/lambda;
        v1 <- v*eldt2+lambda*vbarp*psi;
        v2 <- (v1 > 0) * v1; # Take v2 = 0 if v1<0, else v2=v1
        par <- sqrt(v2) + eta/2 * sqrt(dt)*W2;
        vf <- eldt2*par*par +lambda*vbarp*psi + v1 - v2;
                                # Full truncation

        # Log-stock process (Andersen equation (33))
        vvf <- (v+vf > 0) * (v+vf);
        dw <- vvf/2*dt;
        x <- x  - dw/2 + rho2m1*sqrt(dw)*W1 +
            rho/eta*(lambda*dw + vf-v -lambda*vbar*dt) ;
        # Impose martingale constraint
        x <- x - log(mean(exp(x)));
        v <- vf;
        return(cbind(x,v));
}
```

Once again, here's how to run the code:

In [22]:
```
HestonMC2(paramsBCC)(S0=1, T=1, AK=strikes, N=100000, m=4, evolve=evol
veAlfonsiF, exactVols=exactHestonVolsBCC)
```

Out[22]:

	Strikes	Paths	Steps	ivol	bias	twoSd	ivolm
1	0.8	1e+05	8	0.2287799	-0.0002158135	0.004389728	0.2283266
2	1.0	1e+05	8	0.1813934	-0.0003347400	0.001561587	0.1811047
3	1.2	1e+05	8	0.1522542	0.0002064202	0.001122176	0.1524356

	ivolRichardson	biasRichardson	twoSdRichardson
1	0.2292324	2.366572e-04	0.004519027
2	0.1816821	-4.603280e-05	0.001634922
3	0.1520724	2.466899e-05	0.001208573

Convergence of Alfonsi scheme with full truncation and BCC2 parameters

In [23]:
```
tmp <- resFAndersen.BCC2
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="green4",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="green4",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resAlfonsiF.BCC2
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="deeppink2",ylab="Implied
volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, "
(Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="deeppink2",lt
y=2)
```

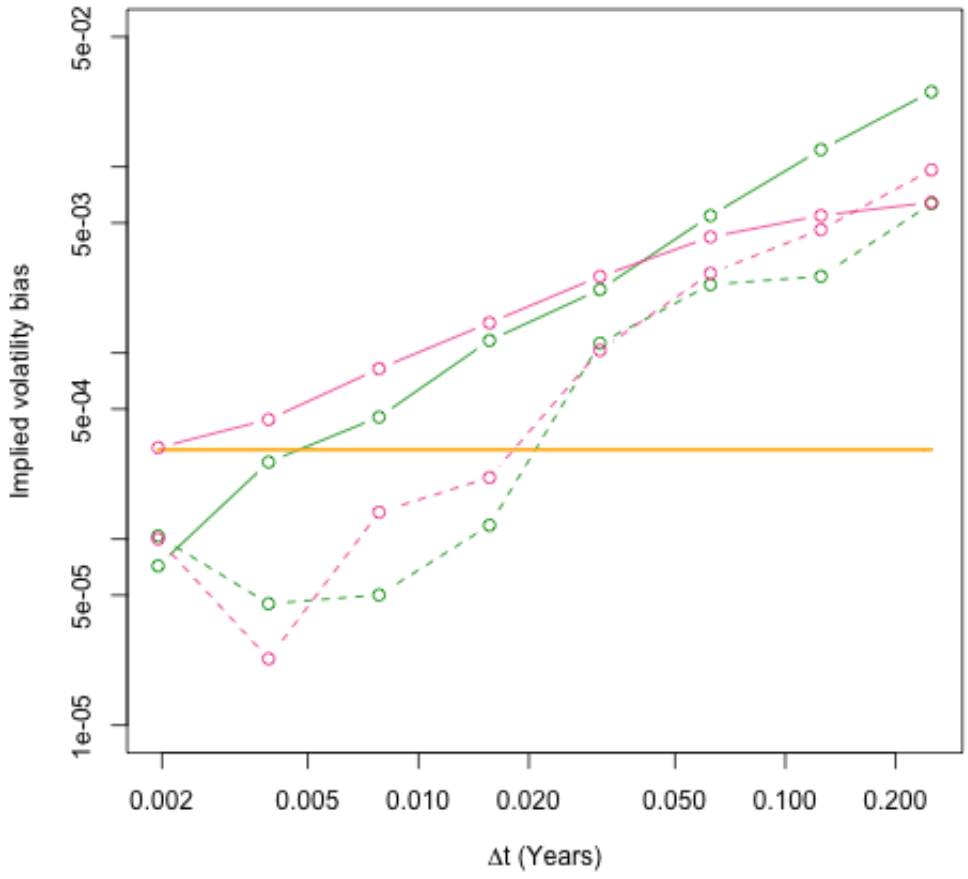

Figure 7: Euler with full truncation and Andersen x-discretization in green; Alfonsi with full truncation in pink; dashed lines are with Richardson extrapolation ($T = 1$, $K = 1.2$)

- Now the problem with Alfonsi is fixed!

Convergence of moments

Recall from Lecture 3 that in the Heston model,

$$\hat{v}_{t+\Delta} := \mathbb{E}\left[v_{t+\Delta}|v_t\right] = \bar{v} + \left(v_t - \bar{v}\right) e^{-\lambda\,\Delta}$$

and

$$\begin{aligned} Var\left[v_{t+\Delta}|v_t\right] &= \int_t^{t+\Delta} e^{-2\,\lambda\,(T-t)}\,\eta^2\,\hat{v}_s\,dt \\ &= \frac{\eta^2}{\lambda}\left(1 - e^{-\lambda\,\Delta}\right)\left[e^{-\lambda\,\Delta}\,v_t + \frac{1}{2}\left(1 - e^{-\lambda\,\Delta}\right)\,\bar{v}\right] \end{aligned}$$

We can show that if $\tilde{v}$ denotes the Alfonsi (2010) discretization (4), we have

$$\mathbb{E}[\tilde{v}_{t+\Delta}|v_t] = \mathbb{E}[v_{t+\Delta}|v_t] + \mathcal{O}(\Delta^3)$$

and

$$Var[\tilde{v}_{t+\Delta}|v_t] = Var[v_{t+\Delta}|v_t] + \mathcal{O}(\Delta^3)$$

Richardson extrapolation again

Suppose now that our scheme has order 2 weak convergence and so generates an estimate of the true value of a claim as follows:

$$\mathbb{E}\left[g(\hat{X}_T)\right] = \mathbb{E}\left[g(X_T)\right] + c\,\Delta^2 + \mathcal{O}(\Delta^3)$$

where $\hat{X}$ is the discretization.

Then we have

$$4\,\mathbb{E}\left[g\left(\hat{X}_T^{\Delta}\right)\right] - \mathbb{E}\left[g\left(\hat{X}_T^{2\,\Delta}\right)\right] = 3\,\mathbb{E}\left[g(X_T)\right] + \mathcal{O}(\Delta^3)$$

- Convergence does look quadratic for our Euler discretizations with BCC parameters so Richardson extrapolation might work in this case.
- However, convergence seems to be sublinear in the BCC2 case, and quadratic Richardson will not work there.

Explaining the Alfonsi scheme

- How could Alfonsi have been so smart as to pick this particular discretization where errors cancel to $\mathcal{O}(\Delta^2)$?
  - Answer: He implemented a scheme due to Ninomiya and Victoir (NV).
- [Ninomiya and Victoir][4] showed in complete generality that their scheme has second order weak convergence.
  - In particular, the mean and variance of the discretized process must be accurate to second order in the timestep.
  - Alfonsi uses NV discretization only for the variance process.

Operator splitting

- Suppose we have two operators (matrices A_1 and A_2 say) that don't commute in general.
- Write the solution to the ODE

$$\frac{dx}{dt} = A\,x$$

as

$$x(t) = e^{A\,t}\,x(0).$$

- Now split the operator as $A = A_1 + A_2$. Then

$$e^{A\,t}\,x(0) \neq e^{A_1\,t}\,e^{A_2\,t}\,x(0)$$

The Baker-Campbell-Hausdorff formula

From Wikipedia, the Baker-Campbell-Hausdorff formula is the solution to

$$Z = \log e^X\,e^Y$$

for noncommutative X and Y.

$$Z = X + Y + \frac{1}{2}[X,Y] + \frac{1}{12}[X,[X,Y]] - \frac{1}{12}[Y,[X,Y]] + \ldots$$

The Ninomiya-Victoir (NV) scheme

Suppose we are given a problem of the form

(5)
$$\partial_t f + \left\{ V_0 + \frac{1}{2} \sum_{i=1}^{n} V_i^2 \right\} f = 0$$

(the diffusion equation for example) where the V_i are first order differential operators.

Then, according to [Ninomiya and Victoir][8], a second order weak solution is given by simulation with a step

$$\mathbf{x}_{t+\Delta} = \begin{cases} e^{V_0 \, \Delta/2} \, e^{V_1 \, \sqrt{\Delta} \, Z_1} \, e^{V_2 \, \sqrt{\Delta} \, Z_2} \, \ldots \, e^{V_n \, \sqrt{\Delta} \, Z_n} \, e^{V_0 \, \Delta/2} \, \mathbf{x}_t & \text{if } \Lambda_t = 1 \\ e^{V_0 \, \Delta/2} \, e^{V_n \, \sqrt{\Delta} \, Z_n} \, \ldots \, e^{V_2 \, \sqrt{\Delta} \, Z_2} \, e^{V_1 \, \sqrt{\Delta} \, Z_1} \, e^{V_0 \, \Delta/2} \, \mathbf{x}_t & \text{if } \Lambda_t = 0 \end{cases}$$

where the Z_i are independent $N(0,1)$ random variables, and Λ_t is a Bernoulli random variable with $p = 1/2$.

- This looks like a mixture of Strang splitting and Symmetrically Weighted Sequential Splitting (SWSS).

Splitting methods

Consider the initial value problem

(6)
$$\frac{dx}{dt} = (A_1 + A_2)\, x$$

where A_1 and A_2 are differential operators.

- The true solution to (6) over some small interval Δ is
$$x(t+\Delta) = e^{(A_1+A_2)\,\Delta}\, x(t).$$
- *Strang splitting* is the approximation
$$x(t+\Delta) \approx e^{A_1 \, \Delta/2} \, e^{A_2 \, \Delta} \, e^{A_1 \, \Delta/2} \, x(t).$$
- *SWSS splitting* is the approximation
$$x(t+\Delta) \approx \frac{1}{2} \left\{ e^{A_1 \, \Delta} \, e^{A_2 \, \Delta} + e^{A_2 \, \Delta} \, e^{A_1 \, \Delta} \right\} \, x(t).$$
- Both of these splitting methods have errors of order Δ^3.

Cubature on Wiener space of degree 3

- *Cubature on Wiener space* of degree 3 discretizes the process as

(7)
$$x_{s+\Delta} = \exp\left\{\Delta\, V_0 + \sqrt{\Delta}\, Y_s\, V_1\right\} x_s$$

where
$$V_0 = \mu(x,t)\,\partial_t;\; V_1 = \sigma(x,t)\,\partial_x.$$

- The LHS of (7) is then understood as a solution of the ODE
$$dy_t = V_0(y_t,t)\,dt + V_1(y_t,t)\,dZ_t.$$

Relationship to Euler-Maruyama

- Taylor expanding the exponential in (7):
$$x_{s+\Delta} = \exp\left\{\Delta\, V_0 + \sqrt{\Delta}\, Y_s\, V_1\right\} x_s$$
to first order gives
$$x_{s+\Delta} = x_s + \left\{\Delta\, V_0 + \sqrt{\Delta}\, Y_s\, V_1\right\} x_s = x_s + \mu\,\Delta + \sigma\,\sqrt{\Delta}\, Y_s$$
which is just the Euler-Maruyama scheme again.

- The point is that an exact solution of (7) or a better approximation to (7) may lead to better convergence.

- The ODE may be solved exactly (if lucky or smart) or numerically using a Runge-Kutta scheme for example.
  - Again, MC or QMC methods would be used in practice to compute the expectation.

Summary of the cubature method

- Write the backward equation for the claim to be valued in the form
$$\partial_t f(S,t) + \mathcal{L} f(S,t) = 0$$
with $f(S_T,T) = g(S_T)$ where
$$\mathcal{L} = V_0 + \frac{1}{2}\sum_i V_i^2$$
is the infinitesimal generator of the Itô diffusion.

- Then

$$f(S,t) = \mathbb{E}_t\left[g(S_T)\right]$$

where S_T is obtained as the ODE solution

$$S_T = \exp\left\{(T-t)\,V_0 + \sum_i \sqrt{T-t}\,Z_i V_i\right\} S.$$

Example: The Bachelier model

- The Bachelier SDE is

$$dS_t = \sigma\, dZ_t.$$

- The corresponding backward equation is

$$\partial_t f(S,t) + \frac{\sigma^2}{2}\partial_{S,S} f(S,t) = 0 =: \partial_t f(S,t) + \frac{1}{2}\,V_1^2\, f(S,t) = 0$$

with $V_1 = \sigma\,\partial_S$.

- Applying Feynman-Kac, the value of an option is given by $\mathbb{E}\left[g(S_T)\right]$ for some payoff function $g(\cdot)$.

Solution using cubature on Wiener space

- Using cubature, $\mathbb{E}\left[g(S_T)\right]$ may be approximated as an average over the

$$S_T = e^{\mathcal{L}\,\sqrt{T-t}\,Y} S(t).$$

The S_T are solutions of the ODE

$$\frac{d}{du}S(u) = \mathcal{L}S(u) = \sigma\partial_S S(u) = \sigma$$

evaluated at the random times $u = \sqrt{T-t}\,Y$ where the law of Y is some approximation to the law of $Z \sim N(0,1)$.

- The solution is of course just $S_T = S + \sigma\sqrt{T-t}\,Y$ so that

$$f(S,t) = \mathbb{E}\left[g(S + \sigma\sqrt{T-t}\,Y)\right].$$

Solution for European call option

- If $g(S_T) = (S_T - K)^+$, we obtain

$$C(S,t) = \mathbb{E}\left[(S_T - K)^+\right] = \mathbb{E}\left[(S + \sigma\sqrt{T-t}\,Y - K)^+\right].$$

  where Y could be for example binomial.
  - Recall that cubature in finite dimensions involves picking points and weights to as to integrate exactly some functions of chosen form (such as polynomials up to some order or Gaussians).

- Note that we don't need cubature to compute the RHS; the expectation may be computed explicitly in this case.

Intuition for Ninomiya-Victoir: Feynman-Kac

The solution of (5):

$$\partial_t f + \left\{ V_0 + \frac{1}{2}\sum_{i=1}^{n} V_i^2 \right\} f = 0$$

with $f(x_T, T) = g(x_T)$ may be written formally as $f(x,t) = \mathbb{E}\left[g(x_T)\right]$ where

$$\begin{aligned} x_T &= \exp\left\{ V_0\,(T-t) + \sum_i V_i\,\sqrt{T-t}\,Z_i \right\} x \\ &\approx \prod_{j=1}^{n} \exp\left\{ V_0\,\Delta + \sum_i V_i\,\sqrt{\Delta}\,Z_{ij} \right\} x \end{aligned}$$

where n is the number of time steps, and $\Delta = (T-t)/n$.

- The Ninomiya-Victoir scheme involves evaluating the solutions of ODEs over deterministic and random time intervals Δ and $\sqrt{\Delta}\,Z_{ij}$ respectively.

Intuition for Ninomiya-Victoir: Splitting

Consider two non-commuting operators (or matrices) A and B. Then

$$(A+B)(A+B) = A^2 + A\,B + B\,A + B^2$$

and

$$\begin{aligned} e^{(A+B)\,\Delta} &= \frac{1}{2}\left[e^{A\,\Delta}\,e^{B\,\Delta} + e^{B\,\Delta}\,e^{A\,\Delta}\right] + \mathcal{O}(\Delta^3) \\ \text{LHS} &= 1 + (A+B)\,\Delta + \frac{1}{2}(A+B)^2\,\Delta^2 + \mathcal{O}(\Delta^3) \\ \text{RHS} &= 1 + (A+B)\,\Delta + \frac{1}{2}\,A^2\,\Delta^2 + \frac{1}{2}\,B^2\,\Delta^2 \\ &\quad + \frac{1}{2}\,(A\,B + B\,A)\,\Delta^2 + \mathcal{O}(\Delta^3) \end{aligned}$$

Similarly

$$e^{(A+B)\,\Delta} = e^{A\,\Delta/2}\,e^{B\,\Delta}\,e^{A\,\Delta/2} + \mathcal{O}(\Delta^3)$$

Intuition for Ninomiya-Victoir: Randomization

- Randomization in the Ninomiya-Victoir (NV scheme) has the effect of ensuring that pairs of operators appear in forward and reverse orders.
  - Expanding the expectation gives terms like

$$\begin{aligned} &\mathbb{E}\left[\left(\Lambda\,V_i^2\,V_j^2\,\Delta^2 + (1-\Lambda)\,V_j^2\,V_i^2\,\Delta^2\right)\mathbf{x_t}\right] \\ &= \frac{1}{2}\,\mathbb{E}\left[\left(V_i^2\,V_j^2\,\Delta^2 + V_j^2\,V_i^2\,\Delta^2\right)\,\mathbf{x_t}\right] \end{aligned}$$

  - To order Δ^2, this gives agreement with the expansion of $e^{\frac{1}{2}V_i^2\,\Delta + \frac{1}{2}V_j^2\,\Delta}\,\mathbf{x}_t$.
  - Higher order terms such as $V_i^2\,V_j^2\,V_k^2\,\Delta^3$ also appear in forward and reverse orders but this is not consistent with the expansion of $e^{\frac{1}{2}V_i^2\,\Delta + \frac{1}{2}V_j^2\,\Delta + \frac{1}{2}V_k^2\,\Delta}\,\mathbf{x}_t$.
- It may be explicitly checked that the scheme is second order.

Example: The Heston variance process

The Heston variance SDE reads

$$dv = \lambda\,(v - \bar{v})\,dt + \eta\,\sqrt{v}\,dZ$$

Applying Itô's Lemma, functions $f(v,t)$ satisfy the equation

$$\begin{aligned}\frac{df}{dt} &= -\lambda(v-\bar{v})\,\partial_v f + \frac{\eta^2}{2}\,v\,\partial_{v,v} f \\ &= \left(V_0 + \frac{1}{2}\,{V_1}^2\right) f(v,t)\end{aligned}$$

and $V_0 = \left[-\lambda\,(v-\bar{v}) - \eta^2/4\right]\partial_v;\ V_1 = \eta\,\sqrt{v}\,\partial_v.$

Example: The Heston variance process

Now choose $f(v,t) = v$. Then $e^{V_0\,\Delta} v(0)$ is the solution of the ODE

$$\frac{dv}{dt} = V_0 v = \left[-\lambda\,(v-\bar{v}) - \eta^2/4\right]\partial_v v = -\lambda\,(v-\bar{v}) - \eta^2/4$$

which is

$$v(t) = \bar{v}' + (v_0 - \bar{v}')\,e^{-\lambda\,\Delta}$$

where

$$\bar{v}' = \frac{\lambda\,\bar{v} - \eta^2/4}{\lambda}.$$

Likewise, $e^{V_1\,\sqrt{\Delta}\,Z} v(0)$ is the solution of the ODE

$$\frac{dv}{ds} = V_1 v = \eta\,\sqrt{v}$$

evaluated at the time $s = \sqrt{\Delta}\,Z$ which is

$$e^{V_1\,\sqrt{t}\,Z} v(0) = \left(\sqrt{v_0} + \frac{\eta}{2}\,\sqrt{\Delta}\,Z\right)^2.$$

The Heston variance process: A NV timestep

One NV timestep of length Δ is then evaluated as follows:

1.
$$v_1 := e^{V_0\,\Delta/2} v_t = \bar{v}' + (v_t - \bar{v}')\, e^{-\lambda\,\Delta/2}$$

2.
$$v_2 := e^{V_1\,\sqrt{\Delta}\,Z} v_1 = \left(\sqrt{\bar{v}' + (v_t - \bar{v}')\, e^{-\lambda\,\Delta/2}} + \frac{\eta}{2}\sqrt{\Delta}\,Z\right)^2$$

3.
(8)
$$\begin{aligned} v_{t+\Delta} &= e^{V_0\,\Delta/2} v_2 = \bar{v}' + (\bar{v}' - v_2)\, e^{-\lambda\,\Delta/2} \\ &= \bar{v}' + \left[\left(\sqrt{\bar{v}' + (v_t - \bar{v}')\, e^{-\lambda\,\Delta/2}} + \frac{\eta}{2}\sqrt{\Delta}\,Z\right)^2 - \bar{v}'\right]\, e^{-\lambda\,\Delta/2} \end{aligned}$$

It is easy to show that (4) and (8) are equivalent.

The Heston SDE again

The Heston SDE may be written in the form

$$\begin{aligned} dx &= -\frac{v}{2}\,dt + \sqrt{v}\,dZ \\ dv &= -\lambda\,(v - \bar{v})\,dt + \eta\sqrt{v}\,\left\{\rho\,dZ + \sqrt{1-\rho^2}\,dZ^{\perp}\right\} \end{aligned}$$

Applying Itô's Lemma as before, functions $f(x, v, t)$ satisfy the equation

$$\frac{df}{dt} + \mathcal{L}f = 0$$

with

$$\mathcal{L}f = -\frac{1}{2}\,v\,\partial_x f - \lambda(v - \bar{v})\,\partial_v f + \frac{1}{2}\,v\,\partial_{x,x} f + \rho\,\eta\,v\,\partial_{x,v}\,f + \frac{\eta^2}{2}\,v\,\partial_{v,v} f.$$

Operator splitting again

$\mathcal{L}$ can be rewritten in the form

$$\mathcal{L} = V_0 + \frac{1}{2} V_1^2 + \frac{1}{2} V_2^2$$

with

$$\begin{aligned} V_0 &= \left[-\lambda (v - \bar{v}) - \frac{1}{4} \eta^2\right] \partial_v - \left(\frac{1}{2} v + \frac{1}{4} \rho \eta\right) \partial_x \\ V_1 &= \sqrt{v}\, \partial_x + \rho \eta \sqrt{v}\, \partial_v \\ V_2 &= \sqrt{1 - \rho^2}\, \eta \sqrt{v}\, \partial_v. \end{aligned}$$

The solution may be written formally as:

$$f(x, v, t) = e^{\left\{V_0 + \frac{1}{2} V_1^2 + \frac{1}{2} V_2^2\right\} t} f(x_0, v_0, 0)$$

The Ninomiya-Victoir recipe again

Let $f(x, v, t)$ be the state vector $\begin{pmatrix} x \\ v \end{pmatrix} =: \mathbf{x}$.

Then, according to Ninomiya-Victoir, a second order weak solution is given by simulating with the discretization:

$$\mathbf{x}_{t+\Delta} = \begin{cases} e^{V_0 \Delta/2}\, e^{V_1 \sqrt{\Delta}\, Z}\, e^{V_2 \sqrt{\Delta}\, Z^\perp}\, e^{V_0 \Delta/2}\, \mathbf{x}_t & \text{if } \Lambda_t = 1 \\ e^{V_0 \Delta/2}\, e^{V_2 \sqrt{\Delta}\, Z^\perp}\, e^{V_1 \sqrt{\Delta}\, Z}\, e^{V_0 \Delta/2}\, \mathbf{x}_t & \text{if } \Lambda_t = 0 \end{cases}$$

where Λ_t is a Bernoulli random variable with probability $1/2$,and Z and $Z^\perp$ are independent $N(0, 1)$ random variables.

The full Heston process: A NV timestep

The first set of ODEs to solve is

$$\begin{aligned}\frac{dx}{dt} &= -\frac{v}{2} - \frac{\rho\,\eta}{4} \\ \frac{dv}{dt} &= -\lambda\,(v-\bar{v}) - \frac{1}{4}\,\eta^2\end{aligned}$$

The solution gives the first operation in the NV timestep as follows:

1.
$\mathbf{x}_1 := e^{V_0\,\Delta/2}\mathbf{x}_t = e^{V_0\,\Delta/2}\,(\,x_t\;v_t\,) = \left(\,x_t - \left(\frac{1}{2}\,\bar{v}' + \frac{1}{4}\,\rho\,\eta\right)\,\Delta/2 - \frac{1}{2}\,(v_t-\bar{v}')\,\psi(\Delta/2)\,\bar{v}' +$
where

$$\psi(x) = \frac{1-e^{-\lambda\,x}}{\lambda}.$$

The second set of ODEs to solve is

$$\begin{aligned}\frac{dx}{dt} &= \sqrt{v} \\ \frac{dv}{dt} &= \rho\,\eta\,\sqrt{v}\end{aligned}$$

The solution gives the second operation in the NV timestep as follows:

2.

$$\begin{aligned}\begin{pmatrix}x_2\\ v_2\end{pmatrix} &= e^{V_1\,\sqrt{\Delta}\,Z}\begin{pmatrix}x_1\\ v_1\end{pmatrix} \\ &= \begin{pmatrix}x_1 + \frac{\left(\sqrt{v_1}+\frac{1}{2}\rho\,\eta\,\sqrt{\Delta}Z\right)_+^2 - v_1}{\rho\,\eta}\,\sqrt{\Delta}\,Z \\ \left(\sqrt{v_1}+\frac{1}{2}\rho\,\eta\,\sqrt{\Delta}\,Z\right)_+^2\end{pmatrix}\end{aligned}$$

The third set of ODEs to solve is

$$\frac{dv}{dt} = \sqrt{1-\rho^2}\,\eta\sqrt{v}$$

The solution gives the third operation in the NV timestep as follows:

3.

$$\begin{pmatrix} x_3 \\ v_3 \end{pmatrix} = e^{V_2\sqrt{\Delta}\,Z}\begin{pmatrix} x_2 \\ v_2 \end{pmatrix} = \begin{pmatrix} x_2 \\ \left(\sqrt{v_2} + \frac{1}{2}\rho\,\eta\sqrt{\Delta}\,Z^{\perp}\right)_+^2 \end{pmatrix}$$

So that, if $\Lambda_t = 1$,

4.

$$\mathbf{x}_{t+\Delta} = e^{V_0\,\Delta/2}\,(\,x_3\;v_3\,) = \left(x_3 - \left(\tfrac{1}{2}\,\bar{v}' + \tfrac{1}{4}\,\rho\,\eta\right)\,\Delta/2 - \tfrac{1}{2}\,(v_3-\bar{v}')\,\psi(\Delta/2)\,\bar{v}' + (v_3-\bar{v}')\right.$$

We follow the same procedure in reverse if $\Lambda = 0$.

- Note that this scheme is somewhat more complicated than Andersen's, but shouldn't really take longer to run

Ninomiya-Victoir code

In [24]:
```
evolveNV <- function(v,x,dt,W1,W2,L){

        eldt2 <- exp(-lambda*dt/2)
        sqrtdt <- sqrt(dt)
        psi <- (1-exp(-lambda*dt/2))/lambda

            #Evolve x and v together forwards: L0-L1-L2-L0
            x1 <- x - (vbarp/2+rho*eta/4)*dt/2-(v-vbarp)/2*psi
            v1 <- vbarp + (v-vbarp)*eldt2

            par1 <- sqrt(v1) + rho*eta/2*sqrtdt*W1
            sqrtv2 <- (par1>0)*par1# Same choice as Friz et al.
            v2 <- sqrtv2*sqrtv2
            x2 <- x1+(v2-v1)/(rho*eta)

            x3 <- x2
            par1 <- sqrtv2 + rho2m1*eta/2*sqrtdt*W2
            sqrtv3 <- (par1>0)*par1 # Same choice as Friz et al.
            v3 <- sqrtv3*sqrtv3

            xfwd <- x3 - (vbarp/2+rho*eta/4)*dt/2-(v3-vbarp)/2*psi
            vfwd <- vbarp + (v3-vbarp)*eldt2

            #Evolve x and v together backwards:  L0-L2-L1-L0
            x1 <- x - (vbarp/2+rho*eta/4)*dt/2-(v-vbarp)/2*psi
            v1 <- vbarp + (v-vbarp)*eldt2

            x2 <- x1
            par1 <- sqrt(v1) + rho2m1*eta/2*sqrtdt*W2
            sqrtv2 <- (par1>0)*par1 # Same choice as Friz et al.
            v2 <- sqrtv2*sqrtv2

            par1 <- sqrtv2 + rho*eta/2*sqrtdt*W1;
            sqrtv3 <- (par1>0)*par1 # Same choice as Friz et al.
            v3 <- sqrtv3*sqrtv3
            x3 <- x2+(v3-v2)/(rho*eta)

            xbwd <- x3 - (vbarp/2+rho*eta/4)*dt/2-(v3-vbarp)/2*psi
            vbwd <- vbarp + (v3-vbarp)*eldt2

        xf <- xfwd*L + xbwd*(1-L) #Forwards if L=1 else backwards
        x <- xf - log(mean(exp(xf))) # Martingale constraint
        v <- vfwd*L + vbwd*(1-L) #Forwards if L=1 else backwards

        return(cbind(x,v))
}
```

And here's an example:

In [25]:
```
HestonMC2(paramsBCC)(S0=1, T=1, AK=strikes, N=1000000, m=4, evolve=evo
lveNV, exactVols=exactHestonVolsBCC)
```

Out[25]:

	Strikes	Paths	Steps	ivol	bias	twoSd	ivolm
1	0.8	1e+06	8	0.2295110	0.0005152424	0.0013810850	0.2303283
2	1.0	1e+06	8	0.1815841	-0.0001440666	0.0004912952	0.1813327
3	1.2	1e+06	8	0.1511892	-0.0008585470	0.0003594480	0.1506828

	ivolRichardson	biasRichardson	twoSdRichardson
1	0.2286909	-0.0003048527	0.0014850245
2	0.1818355	0.0001073259	0.0005487182
3	0.1516932	-0.0003545334	0.0004316586

Convergence of Ninomya-Victoir with BCC parameters

In [26]:
```
tmp <- resFAndersen.BCC
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="green4",ylab="Im
plied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delt
a,t, " (Years)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="green4",lt
y=2)
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)
tmp <- resNV.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="blue",ylab="Implied vola
tility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Ye
ars)")))
points(1/tmp$Steps,abs(tmp$biasRichardson),type="b",col="blue",lty=2)
```

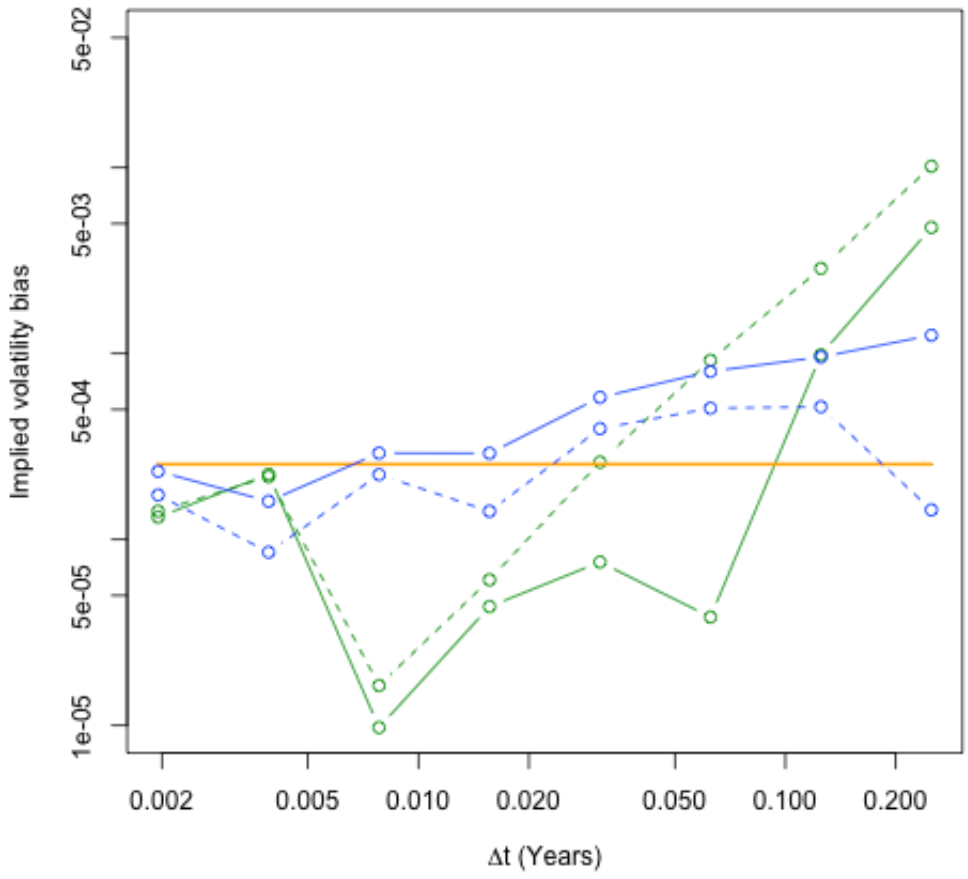

Figure 8: Euler with full truncation and Andersen x-discretization in green; Ninomiya-Victoir in blue; dashed lines are with Richardson extrapolation ($T = 1$, $K = 1.2$)

- Let's leave the fixing of NV for future research...

Summary convergence plot

Now we put results using all schemes so far on the same plot.

In [27]:
```
tmp <- resF.BCC
sdThreshold <- mean(tmp$twoSd)
plot(1/tmp$Steps,abs(tmp$bias),type="b",log="xy",col="purple",ylab="Implied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Years)")))
curve(sdThreshold+x*0,from=1/512, to=1/4,add=T,col="orange",lwd=2)

tmp <- resFAndersen.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="green4",ylab="Implied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Years)")))

tmp <- resAlfonsi.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="deeppink2",ylab="Implied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Years)")))

tmp <- resNV.BCC
lines(1/tmp$Steps,abs(tmp$bias),type="b",col="blue",ylab="Implied volatility bias",ylim=c(0.00001,0.05),xlab=expression(paste(Delta,t, " (Years)")))
```

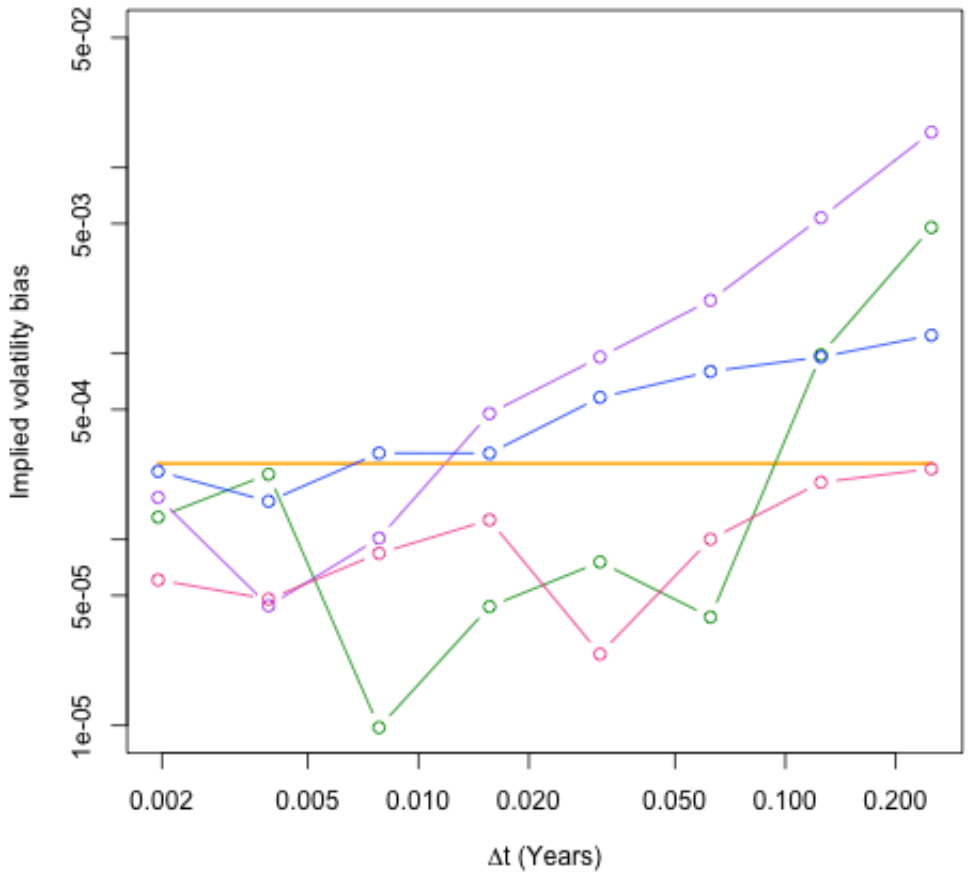

Figure 9: Euler with full truncation in purple; with Andersen x-discretization in green; Alfonsi in pink; Ninomiya-Victoir in blue;

- Let's stick with Alfonsi with full truncation!

More complicated models

- It is typically thought that the Ninomiya-Victoir scheme gives rise to closed form ODE solutions for each time step only in lucky special cases such as Heston.
  - The reason is that the V_0 ODE is typically not soluble in closed-form.
- In [Bayer, Gatheral and Karlsmark][3], we show that we may further split the V_0 operator, writing *e.g.* $V_0 = V_{0,1} + V_{0,2}$ achieving closed-form time steps whilst maintaining $O(\Delta^2)$ accuracy.
  - In particular, we may efficiently simulate much more complicated models such as DMR.
- The form of the kth time step is:

$$
\begin{aligned}
&X\left((k+1)\,\Delta, x\right) \\
&= \begin{cases} e^{\frac{1}{2}\Delta\, V_{0,1}}\, e^{\frac{1}{2}\Delta\, V_{0,2}}\, e^{Z_k^1\, V_1}\, e^{Z_k^2\, V_2}\, e^{Z_k^3\, V_3}\, e^{\frac{1}{2}\Delta\, V_{0,2}}\, e^{\frac{1}{2}\Delta\, V_{0,1}} X(k\,\Delta, x) & \text{if } \Lambda_k = -1 \\ e^{\frac{1}{2}\Delta\, V_{0,1}}\, e^{\frac{1}{2}\Delta\, V_{0,2}}\, e^{Z_k^3\, V_3}\, e^{Z_k^2\, V_2}\, e^{Z_k^1\, V_1}\, e^{\frac{1}{2}\Delta\, V_{0,2}}\, e^{\frac{1}{2}\Delta\, V_{0,1}} X(k\,\Delta, x) & \text{if } \Lambda_k = +1 \end{cases}
\end{aligned}
$$

  where the $Z_k^i \sim N(0, \Delta)$ are independent.

A remark on mathematical innovation driven by applications

- This is the first example in our lecture series of financial applications spurring pure mathematical innovation.
  - Specifically, rough paths theory and the Ninomiya-Victoir scheme.

Quasi-Monte Carlo

- Quasi-Monte Carlo uses low discrepancy sequences instead of random numbers.
  - Low discrepancy sequences distribute points evenly without placing them at regular grid points.
- Monte Carlo converges at rate $\mathcal{O}(1/\sqrt{N})$.
- Under the right conditions, Quasi-Monte Carlo converges at a rate approximately $\mathcal{O}(1/N)$.

Quasi-Monte Carlo in R

In R, quasi-random numbers are just as easy to use as pseudo-random numbers:

In [28]:
```
library(randtoolbox) # This library has the QMC functionality

print(zmc <- rnorm(10)) # generates 10 normal pseudo-random numbers
print(zqmc <- sobol(n=10,dim=4,scram=3,seed=4711,norm=T)) # generates
a 10 x 4 matrix of normal quasi-random numbers
```

```
Loading required package: rngWELL
This is randtoolbox. For overview, type 'help("randtoolbox")'.

 [1]  0.72274574 -0.24159542  1.19935447  0.42876057 -0.80677492  0.0
1726428
 [7]  0.34841920 -0.64014501  2.62656307  0.31987264
            [,1]        [,2]         [,3]        [,4]
 [1,]  0.7548562 -0.71665875 -1.401770664  0.96622222
 [2,]  0.5374604  0.11132384 -0.430229472 -0.73046181
 [3,] -1.2788761 -0.39428055  1.898200769  0.25907372
 [4,]  1.3731449  0.80630613  0.690388634 -1.63730037
 [5,] -0.5832688 -1.28067627 -0.190000436  0.45199060
 [6,] -0.8080373  0.47115094 -0.927083855 -0.64501117
 [7,]  0.2400209 -0.01967126  0.006865142  1.22540384
 [8,] -3.2466265  1.12617028 -0.154345105  0.83815856
 [9,]  0.4643494 -1.63068840  1.107803702 -0.18525837
[10,]  1.1460069  0.61327748  0.280623630  0.03821902
```

Quasi-Monte Carlo code

In [29]:
```
HestonQMC <- function(params){

    is.even <- function(j){as.logical((j+1) %% 2)}

    res <- function(S0, T, AK, N, m, evolve,exactVols=NULL)
    {

    lambda <<- params$lambda
    rho <<- params$rho
    eta <<- params$eta
    vbar <<- params$vbar
    v0 <<- params$v

    n <- m*2 #n is number of timesteps = 2*m so we can use Romberg e
xtrapolation
    sqrt2 <- sqrt(2)
    rho2m1 <<- sqrt(1-rho*rho)
    vbarp <<- vbar - eta^2/(4*lambda)

    negCount <- 0

    # We use a vertical array, one element per M.C. path
    x <- rep(0,N); v <- rep(1,N)*v0
    xm <- x; vm <- v
    W1m <- rep(0,N); W2m <- rep(0,N)

    # Generation of quasi random numbers now takes place outside the
timestep loop
    Z <- sobol(n=N,dim=n,scram=3,seed=4711,norm=T)
      Zperp <- sobol(n=N,dim=n,scram=3,seed=17,norm=T)

    # Loop for bias computation (N small, n big)
    for (i in 1:n)
    {
        # Two sets of correlated normal random vars.

        W1 <- Z[,i] #Take ith column of pre-generated quasi-rvs
        W2 <- Zperp[,i]
        W1 <- W1 - mean(W1); W1 <- W1/sd(W1)
        W2 <- W2 - mean(W2); W2 <- W2/sd(W2)
        # Now W1 and W2 are forced to have mean=0 and sd=1

        W2p <- W2 - cor(W1,W2)*W1 # Eliminate actual correlation
        W2p <- W2p - mean(W2p); W2 <- W2p/sd(W2p)
        # Now W1 and W2 have mean=0, sd=1 and correlation=0

        L <- rbinom(N, size=1, prob=1/2) # Bernoulli rv for NV step

        # Add code for subgrid
        W1m <- W1m + W1/sqrt2; W2m <- W2m + W2/sqrt2 # N(0,1) rv's f
or subgrid
```

```
        if (is.even(i)) {
            resm <- evolve(vm,xm,T/m,W1m,W2m,L)
            xm <- resm[,1]
            vm <- resm[,2]
            W1m <- rep(0,N); W2m <- rep(0,N);
        }

        res <- evolve(v,x,T/n,W1,W2,L)
        x <- res[,1]
        v <- res[,2]

}

  S <- S0*exp(x)
  Sm <- S0*exp(xm)

  # Now we have three vectors of final stock prices
  M <- length(AK);
  AV <- numeric(M); AVdev <- numeric(M);
  BSV <- numeric(M); BSVH <- numeric(M); BSVL <- numeric(M);
  iv2SD <- numeric(M); bias <- numeric(M);
  AVm <- numeric(M); AVmdev <- numeric(M);
  BSVm <- numeric(M); BSVHm <- numeric(M); BSVLm <- numeric(M);
  iv2SDm <- numeric(M);
  AV1 <- numeric(M); AV1dev <- numeric(M);
  BSV1 <- numeric(M); BSVH1 <- numeric(M); BSVL1 <- numeric(M);
  iv2SDrom <- numeric(M);biasRom <- numeric(M);

# Evaluate mean call value for each path
for (i in 1:M)
{
  # 2*m timesteps
  K <- AK[i];
  V <- (S>K)*(S - K); # Boundary condition for European call
  AV[i] <- mean(V);
  AVdev[i] <- sqrt(var(V)/length(V));
  BSV[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i]);
  BSVL[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] - AVdev[i]);
  BSVH[i] <- BSImpliedVolCall(S0, K, T, 0, AV[i] + AVdev[i]);
  iv2SD[i] <- (BSVH[i]-BSVL[i]);

  # m timesteps
  Vm <- (Sm>K)*(Sm - K); # Boundary condition for European call
  AVm[i] <- mean(Vm);
  AVmdev[i] <- sd(Vm) / sqrt(N);
  BSVm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i]);
  BSVLm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] - AVmdev[i]);
  BSVHm[i] <- BSImpliedVolCall(S0, K, T, 0, AVm[i] + AVmdev[i]);
  iv2SDm[i] <- (BSVH[i]-BSVL[i]);

  # Richardson extrapolation estimates
  V1 <- 2*V - Vm
  AV1[i] <- mean(V1)
```

```
    AV1dev[i] <- sd(V1) / sqrt(N)
    BSV1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i])
    BSVL1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] - AV1dev[i])
    BSVH1[i] <- BSImpliedVolCall(S0, K, T, 0, AV1[i] + AV1dev[i])
    iv2SDrom[i] <- (BSVH1[i]-BSVL1[i])

    if(!is.null(exactVols)) {bias <- BSV-exactVols}
    if(!is.null(exactVols)) {biasRom <- BSV1-exactVols}
  }

  data.out <- data.frame(AK,rep(N,M),rep(2*m,M),BSV,bias,iv2SD,BSV
m,BSV1,biasRom,iv2SDrom)
  names(data.out) <- c("Strikes","Paths","Steps","ivol","bias","2s
d","ivolm", "ivolRichardson", "biasRichardson",
                       "2sdRichardson")
  return(data.out)

}
return(res)
}
```

Example of HestonQMC call:

In [30]:
```
HestonQMC(paramsBCC)(S0=1, T=1, AK=strikes, N=100000, m=4, evolve=evol
veNV, exactVols=exactHestonVolsBCC)
```

Out[30]:

	Strikes	Paths	Steps	ivol	bias	2sd	ivolm
1	0.8	1e+05	8	0.2297438	0.0007480732	0.004361094	0.2304267
2	1.0	1e+05	8	0.1815129	-0.0002152532	0.001552826	0.1812508
3	1.2	1e+05	8	0.1511792	-0.0008685494	0.001133325	0.1507949

	ivolRichardson	biasRichardson	2sdRichardson
1	0.2290591	6.333226e-05	0.004688000
2	0.1817749	4.681220e-05	0.001736276
3	0.1515622	-4.856040e-04	0.001367169

Convergence of QMC

- We use the Alfonsi-Andersen discretization with 16 timesteps.
  - The bias was well within our 0.10 vol point tolerance.
- We compute the convergence of Monte Carlo and Quasi Monte Carlo as a a function of N.

Convergence of QMC and MC with BCC parameters

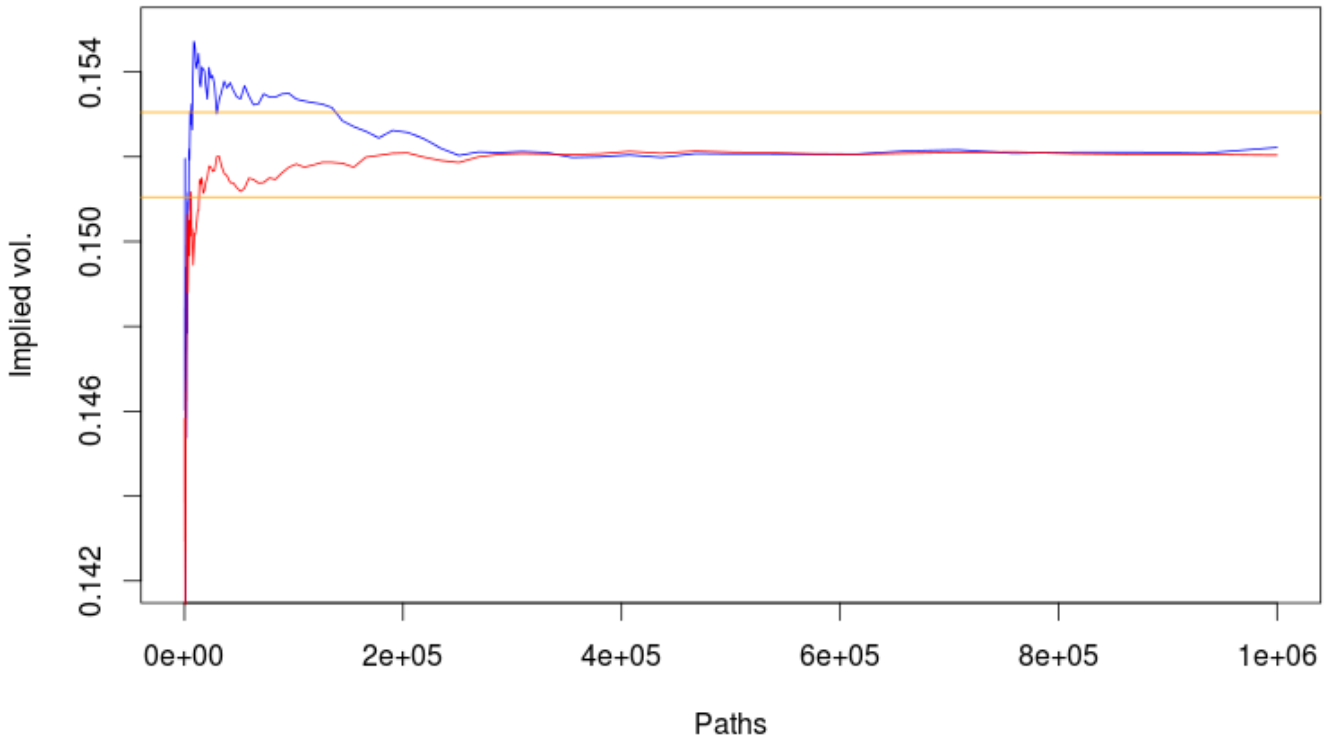

Figure 10: Implied vols for a call ($T = 1$, $K = 1.2$); MC in blue; QMC in red; 0.1 vol point threshold in orange.

Convergence of QMC and MC with BCC parameters: Zoomed

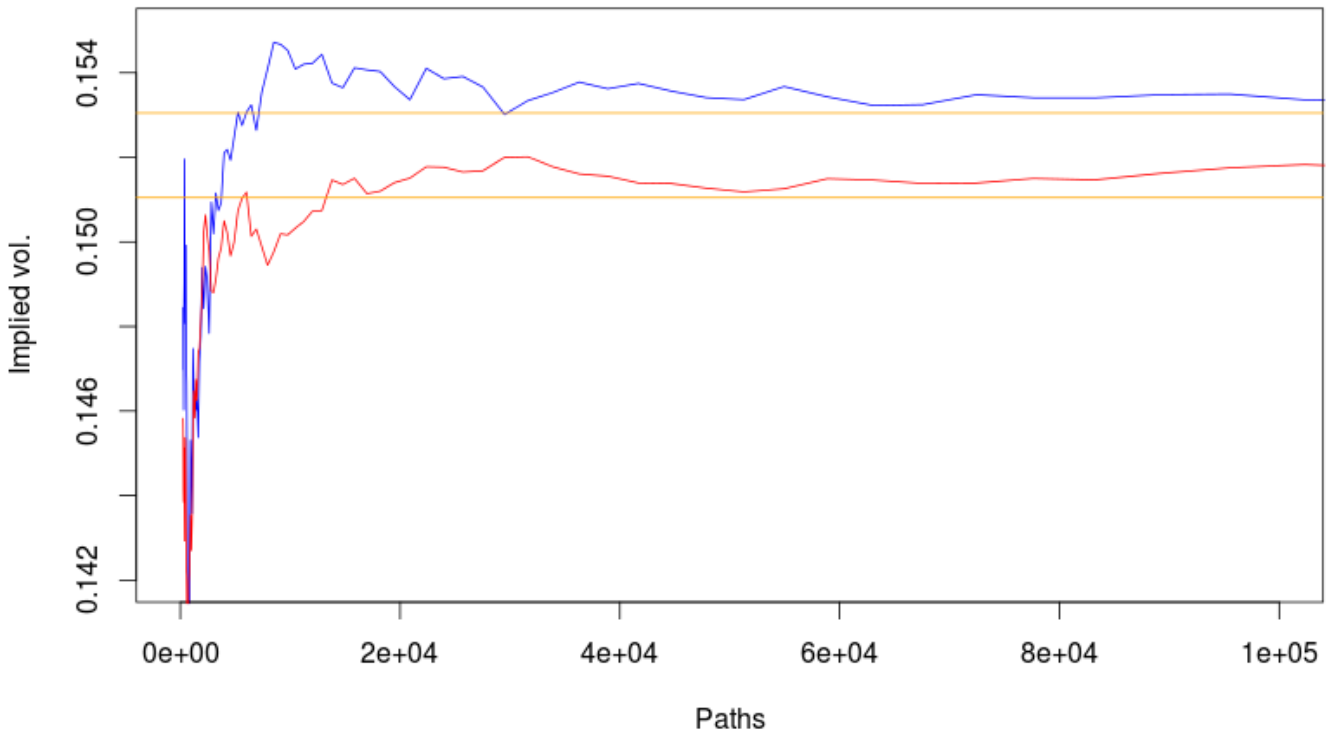

Figure 11: Implied vols for a call ($T = 1$, $K = 1.2$); MC in blue; QMC in red; 0.1 vol point threshold in orange.

QMC vs MC

- Mostly, QMC converges faster than MC.
- However,
  - We can't easily quantify errors as we can with Monte Carlo.
  - QMC may have problems in higher dimensions:
    - The rule-of-thumb is to use no more than 40 dimensions.
    - See the randtoolbox vignette http://cran.r-project.org/web/packages/randtoolbox/randtoolbox.pdf (http://cran.r-project.org/web/packages/randtoolbox/randtoolbox.pdf) for details of how performance has been improved in R by scrambling.

QMC problems in higher dimensions

In [31]:
```
# Sobol in higher dimensions
par(mfrow=c(2,2))
sob0 <- sobol(n=1000,dim=500,scram=0)
sob3 <- sobol(n=1000,dim=500,scram=3)

plot(sob0[,1],sob0[,2])
plot(sob3[,1],sob3[,2])

plot(sob0[,49],sob0[,50])
plot(sob3[,49],sob3[,50])

par(mfrow=c(1,1))
```

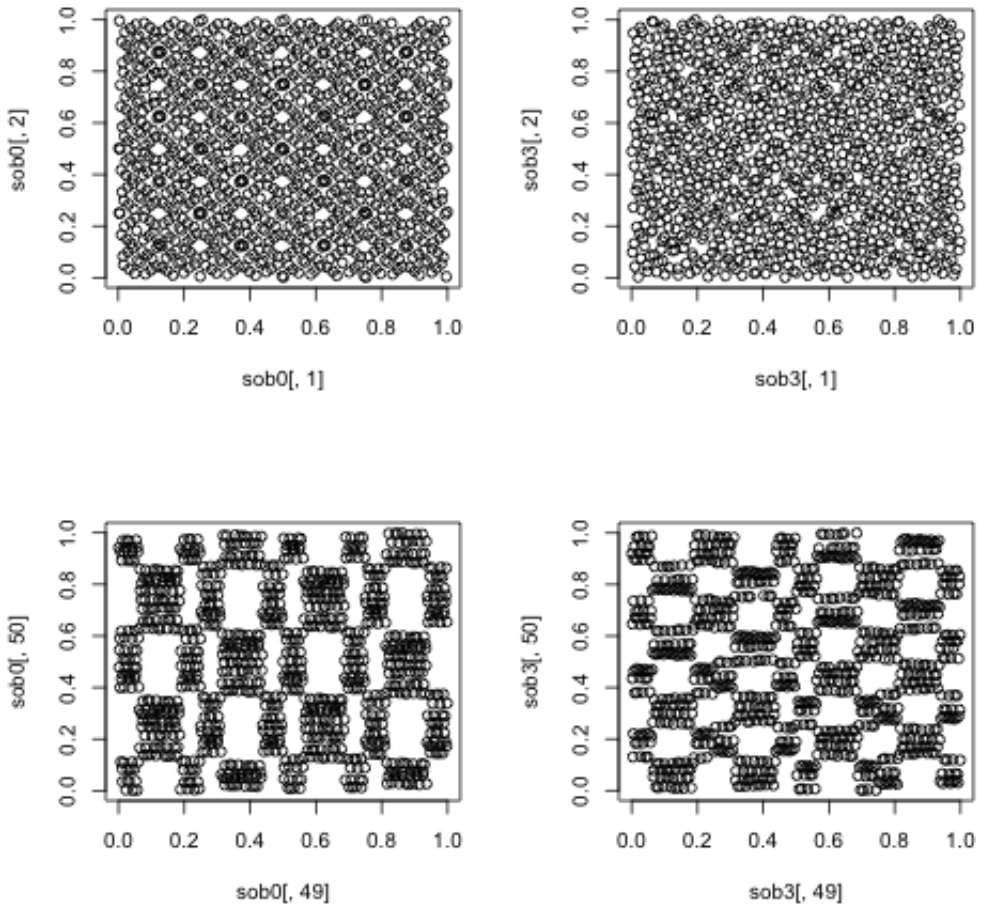

Figure 12: Correlations between dimensions of low discrepancy sequences (Sobol)

No such problem with MC

In [32]:
```
# Compare with rnorm
par(mfrow=c(2,2))
x0 <- array(runif(n=500000),dim=c(1000,500));

plot(x0[,1],x0[,2])
plot(x0[,1],x0[,3])

plot(x0[,49],x0[,50])
plot(x0[,499],x0[,500])

par(mfrow=c(1,1))
```

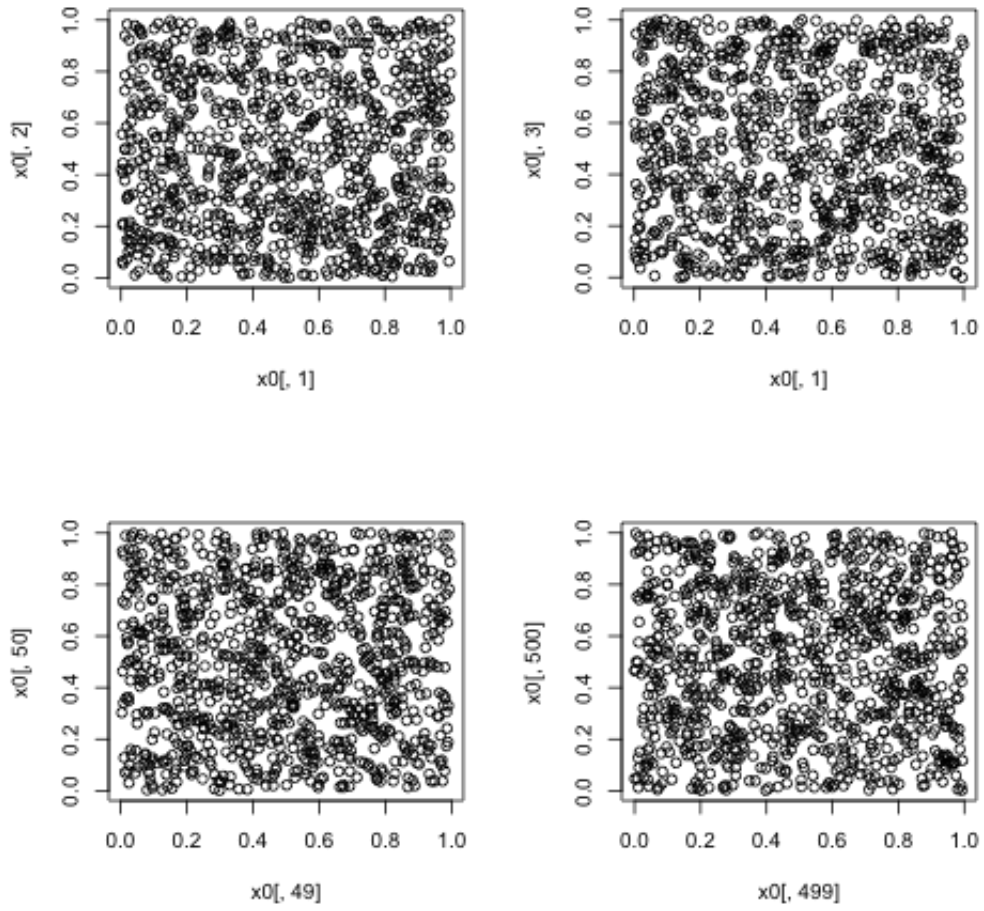

Figure 13: Correlations between pseudo-random numbers

Applications

- Now we have an efficient simulation scheme that we can use to compute various quantities of interest:
  - Alfonsi with full truncation, 16 timesteps; QMC with 25,000 paths.
  - We may want to increase the number of timesteps for path-dependent options.
- To finish the lecture, let's draw some pictures using data generated from MC and QMC

The 1-year implied volatility smile: BCC parameters.

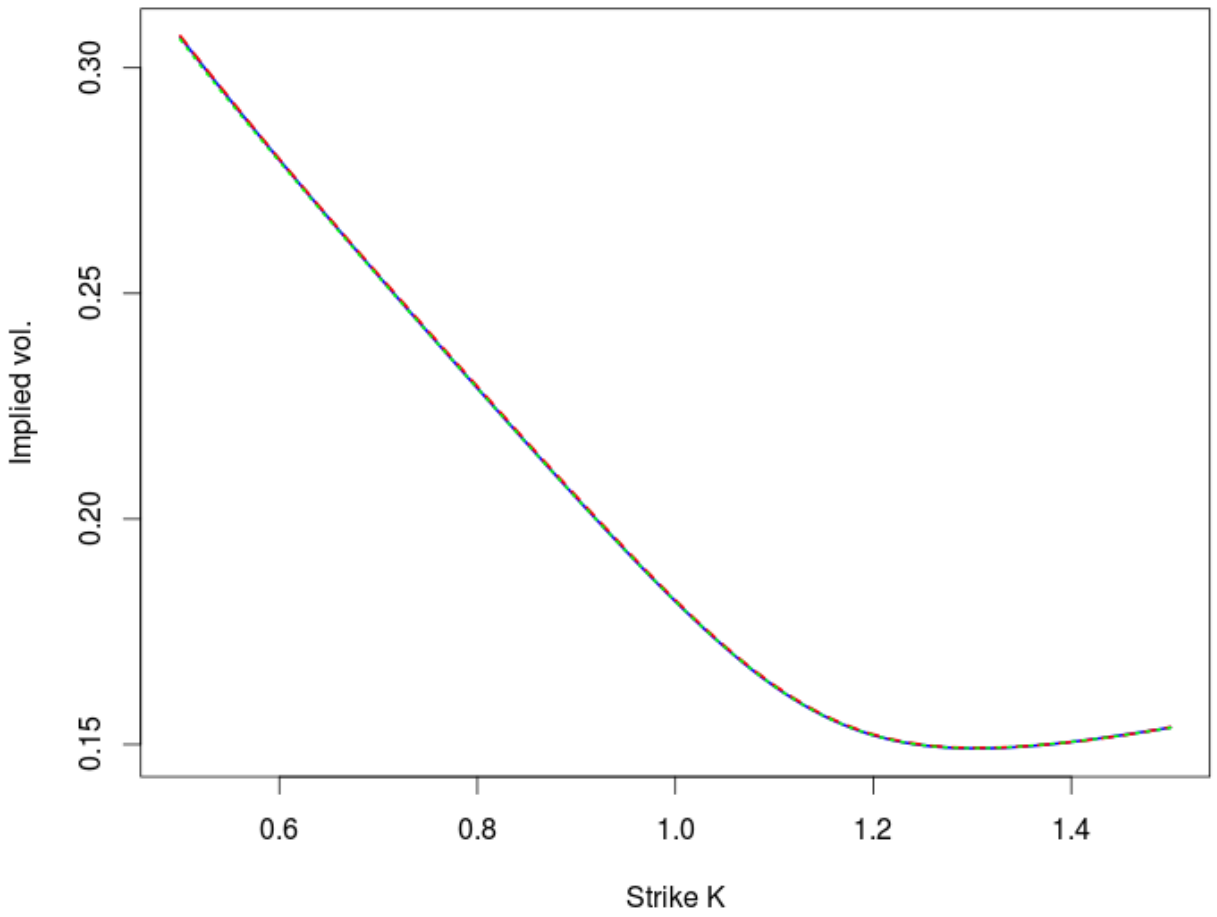

Figure 14: Exact implied vols in blue; MC in red; QMC in green; There's almost no difference when we have 1 million paths!

1-year local and implied variance: BCC parameters

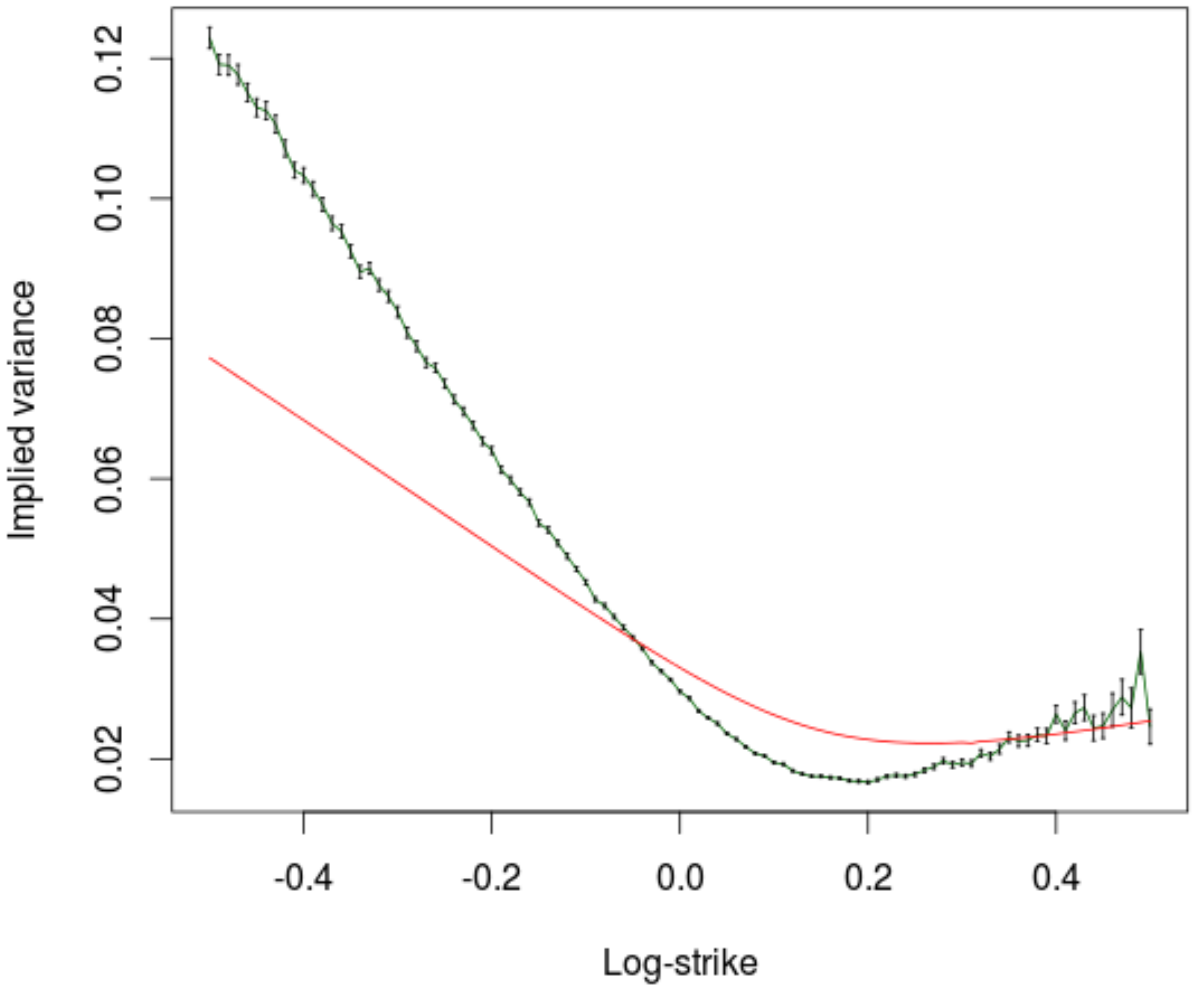

Figure 15: Local variance (dark green) obtained by binning final variance (with error bars); implied variance (red) is superimposed (1 million paths again)

The Heston volatility surface again

First, setup the plot generated from the analytical solution (Lecture 3)

In [33]:
```
k <- seq(-.5,.5,0.05) # Vector of log-strikes
t <- (1:36)/18 # Vector of times
vol1 <- function(k,t){impvolHeston(paramsBCC)(k,t)}
vol2 <- function(k,t){sapply(k,function(k){vol1(k,t)})}
vol <- function(k,t){sapply(t,function(t){vol2(k,t)})}

system.time(zvol <- vol(k,t))
```

Out[33]:
```
   user  system elapsed
  1.019   0.029   1.051
```

Now change the Monte Carlo code to output a matrix of volatilities:

In [34]:
```
HestonSurfaceMC <- function(params){

  res <- function(S0, T, Ak, N, m, evolve)
  {

    M <- length(Ak);
    BSV <- array(dim=c(m,M));
    AV <- numeric(M);

    lambda <<- params$lambda;
    rho <<- params$rho;
    eta <<- params$eta;
    vbar <<- params$vbar;
    v0 <<- params$v;

    n <- m; #n is number of timesteps; No Romberg this time
    sqrt2 <- sqrt(2);
    rho2m1 <<- sqrt(1-rho*rho);
    vbarp <<- vbar - eta^2/(4*lambda);

    # We use a vertical array, one element per M.C. path
    x <- rep(0,N); v <- rep(1,N)*v0;

    # Generation of quasi random numbers now takes place outside the
timestep loop
    Z <- sobol(n=N,dim=n,scram=3,seed=4711,norm=T);
    Zperp <- sobol(n=N,dim=n,scram=3,seed=17,norm=T);

    # Loop over timesteps
    for (i in 1:n)
    {
      # Two sets of correlated normal random vars.

      W1 <- Z[,i]; #Take ith column of pre-generated quasi-rvs
      W2 <- Zperp[,i];
      W1 <- W1 - mean(W1); W1 <- W1/sd(W1);
      W2 <- W2 - mean(W2); W2 <- W2/sd(W2);
      # Now W1 and W2 are forced to have mean=0 and sd=1

      W2p <- W2 - cor(W1,W2)*W1; # Eliminate actual correlation
      W2p <- W2p - mean(W2p); W2 <- W2p/sd(W2p);
      # Now W1 and W2 have mean=0, sd=1 and correlation=0

      res <- evolve(v,x,T/n,W1,W2,L);
      x <- res[,1];
      v <- res[,2];

      S <- S0*exp(x); # Vector of stock prices at time t=T*i/m;

      # Evaluate mean call value for each path
      for (j in 1:M)
      {
```

```
        k <- Ak[j];
        K <- exp(k);
        V <- (S>K)*(S - K); # Boundary condition for European call
        AV[j] <- mean(V);
      }

      BSV[i,] <- BSImpliedVolCall(S0, exp(Ak), T*i/m, 0, AV);    # Co
mpute ith row of output matrix
    }

    res <- list(BSV=BSV,logStrikes=Ak,expiries=seq(0,T,T/m));
  }
  return(res);
}
```

Run this new vol surface code with 50 timesteps and 50,000 paths:

In [35]:
```
system.time(volSurface <- HestonSurfaceMC(paramsBCC)(S0=1, T=2, Ak=k,
N=50000, m=36, evolve=evolveAlfonsiF))
```

Out[35]:
```
   user  system elapsed
  0.827   0.460   1.290
```

Note that the above code is as fast as calling the code with the quasi-closed form solution many times!

Plot the two surfaces together

In [36]:
```
par(mfrow=c(1,2),mex=0.5)
par(oma=c(0,0,0,0))

# First the analytical formula:
z <- (zvol>.10)*zvol+(zvol <= 0.1)*.1

# Add colors
nbcol <- 100
color <- rainbow(nbcol,start=.3,end=.5)
nrz <- nrow(z)
ncz <- ncol(z)
# Compute the z-value at the facet centres
zfacet <- z[-1, -1] + z[-1, -ncz] + z[-nrz, -1] + z[-nrz, -ncz]
# Recode facet z-values into color indices
facetcol <- cut(zfacet, nbcol)

# Generate 3D plot of analytical solution
persp(k, t, z, col=color[facetcol], phi=30, theta=30,
      r=1/sqrt(3)*20,d=5,expand=.5,ltheta=-135,lphi=20,ticktype="detai
led",
      shade=.5,border=NA,xlab="Log-strike k",ylab="Expiration t",zla
b="Implied volatility",main="Heston formula",zlim=c(.1,.35));


# Next the Monte Carlo result

z2 <- t(volSurface$BSV)
z <- (z2>0.05)*z2+(z2<=.1)*.05

# Add colors
nbcol <- 100
color <- rainbow(nbcol,start=.0,end=.2)
nrz <- nrow(z)
ncz <- ncol(z)
# Compute the z-value at the facet centres
zfacet <- z[-1, -1] + z[-1, -ncz] + z[-nrz, -1] + z[-nrz, -ncz]
# Recode facet z-values into color indices
facetcol <- cut(zfacet, nbcol)

# Generate 3D plot of MC solution

persp(k, t, z, col=color[facetcol], phi=30, theta=30,
      r=1/sqrt(3)*20,d=5,expand=.5,ltheta=-135,lphi=20,ticktype="detai
led",
      shade=.5,border=NA,xlab="Log-strike k",ylab="Expiration t",zla
b="Implied volatility",
      main="Monte Carlo",zlim=c(.1,.35))

par(mfrow=c(1,1),mex=1)
```

```
Warning message:
In persp.default(k, t, z, col = color[facetcol], phi = 30, theta = 3
0, : surface extends beyond the boxWarning message:
In persp.default(k, t, z, col = color[facetcol], phi = 30, theta = 3
0, : surface extends beyond the box
```

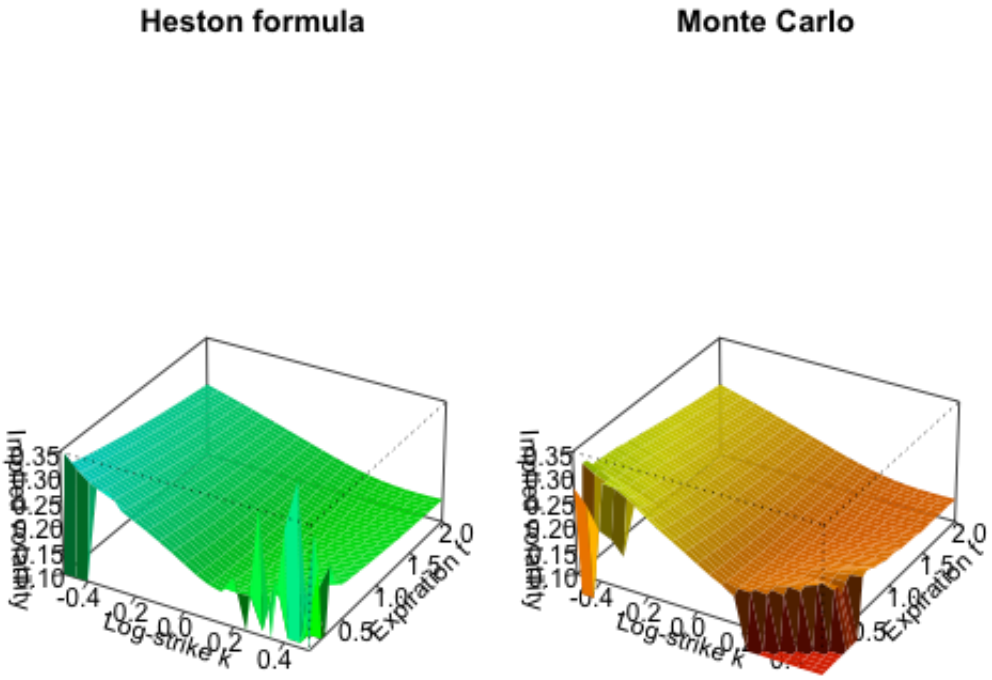

Figure 16: 3D plots of the Heston volatility surface with BCC parameters; Closed-form Heston formula on the left, Monte Carlo on the right.

Summary

- Financial applications are now inspiring (great) mathematicians to find new results.
- These results are already being put to practical use, generating more efficient algorithms.
- Because there is a quasi-closed form formula and because the underlying process is not easy to simulate, the Heston model makes a great test-bed for algorithms.
- Finally, we have a practical (Quasi) Monte Carlo algorithm (Alfonsi with full truncation and Andersen x-discretization) that can be used in later lectures.

References

1. ^ Aurélien Alfonsi, High order discretization schemes for the CIR process: application to affine term structure and Heston models, *Mathematics of Computation* **79**(269), 209–237 (2010).
2. ^ Andersen, Leif B G, Simple and efficient simulation of the Heston stochastic volatility model, *Journal of Computational Finance* **11**(3), 1–42 (2008).
3. ^ Christian Bayer, Jim Gatheral, and Morten Karlsmark, Fast Ninomiya-Victoir calibration of the double-mean-reverting model, *Quantitative Finance* **13**(11), 1813–1829 (2013).
4. ^ Syoiti Ninomiya and Nicolas Victoir, Weak approximation of stochastic differential equations and application to derivative pricing, *Applied Mathematical Finance* **15**(2), 107–121(2008).