# HEDGING OF EUROPEAN TYPE CONTINGENT CLAIMS IN DISCRETE TIME BINOMIAL MARKET MODELS 

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#### Abstract

We consider a discrete-time binomial model of a market consisting of $m \geq 1$ risky securities and one bond. For a European type contingent claim we give an explicit formula for the minimum-cost maximal hedging strategy.


## 1. The main Result

In this note we consider a discrete-time binomail model for a market with $m$ risky securities $S_{1}, \ldots, S_{m}$ and one bond $S_{0}$ with return $R>0$. Time has values $k=0, \ldots, n$, and we write $S_{i}(k)$ for the price of the $i$-th security at time $k$. The model comes with a choice of numbers $0<D_{i}<R<U_{i}$ for each $1 \leq i \leq m$. To describe the random process of the values of $S_{i}$, suppose that the prices of $S_{0}, \ldots, S_{m}$ are known at time $k<n$. Their values at time $k+1$ is determined as follows.
(a) For the bond process,

$$
S_{0}(k+1)=S_{0}(k) \cdot R .
$$

(b) For the remaining securities, flip $m$ coins and according to the results set

$$
S_{i}(k+1)=S_{i}(k) \cdot U_{i} \quad \text { or } \quad S_{i}(k+1)=S_{i}(k) \cdot D_{i}
$$

The coins are not assumed to be independent, nor do the flips at time $k$ and time $k^{\prime} \neq k$. We consider a European contingent claim $X$ with pay-off at time $n$ (of maturity) given by

$$
\begin{equation*}
F=\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(n)-K\right)^{+} \tag{1.1}
\end{equation*}
$$

where $\gamma_{1}, \ldots, \gamma_{n} \geq 0, K \geq 0$ and $x^{+} \stackrel{\text { def }}{=} \max \{x, 0\}$ for any real number $x$.
It is known that the set of rational values of $X$ at time $k$, (i.e its no-arbitrage price range at time $k$, forms an open interval whose upper bound we denote by $C_{\max }(X, k)$. In [1, Section 6 A eqns. (6.1) and (6.2)] we have shown that $C_{\max }(X, k)$ can be expressed solely by means of the prices of $S_{0}, \ldots, S_{m}$ at time $k$ and the parameters of the model (see Proposition 2.6 below).

A minimum cost maximal hedging strategy for $X$ consist of a choice, at each time $k=0, \ldots, n-1$, of numbers $\alpha_{0}(k), \ldots, \alpha_{m}(k)$ which minimize (the cost of the hedging
portfolio)

$$
\begin{equation*}
V_{\alpha}(k)=\sum_{i=0}^{m} \alpha_{i}(k) S_{i}(k) \tag{1.2}
\end{equation*}
$$

subject to the (maximal-hedging) condition that at time $k+1$ the value of this portfolio satisfies

$$
\begin{equation*}
\sum_{i=0}^{m} \alpha_{i}(k) \cdot S_{i}(k+1) \geq C_{\max }(X, k+1) \tag{1.3}
\end{equation*}
$$

In particular the value of the portfolio $V_{\alpha}(k)$ acquired at time $k$ is guaranteed to exceed the value of the option $X$ at time $k+1$. Notice that the values chosen for $\alpha_{i}(k)$ depend on the "state of the world" at time $k$, and in particular on the prices of $S_{0}, \ldots, S_{m}$ at time $k$. In [1, Proposition 4.2] we showed that a minimum cost maximal hedging strategy exists and that its set up cost at each time $k$ is exactly $C_{\max }(X, k)$, namely the maximal rational value of $X$ at time $k$.

The purpose of this note is to give an explicit formula for the values of $\alpha_{0}(k), \ldots, \alpha_{m}(k)$. In the remainder of this section we describe this formula.

For every $1 \leq i \leq m$ set

$$
\begin{equation*}
b_{i}=\frac{R-D_{i}}{U_{i}-D_{i}} \tag{1.4}
\end{equation*}
$$

If necessary, reorder the securities $S_{1}, \ldots, S_{m}$ so that $b_{1}, \ldots, b_{m}$ is non-increasing, namely

$$
\begin{equation*}
b_{1} \geq b_{2} \geq \cdots \geq b_{m} \tag{1.5}
\end{equation*}
$$

Notice that $0<b_{i}<1$ for all $i$. Define for any $0 \leq j \leq m$

$$
q_{j}=\left\{\begin{array}{cl}
1-b_{1} & j=0  \tag{1.6}\\
b_{j}-b_{j+1} & 1 \leq j \leq m-1 \\
b_{m} & j=m
\end{array}\right.
$$

Define for $0 \leq i \leq m$ and for $0 \leq j \leq m$ numbers $\chi_{i}(j)$ as follows

$$
\chi_{0}(j)=R \quad \text { and } \quad \chi_{i}(j)=\left\{\begin{array}{cc}
U_{i} & i \leq j  \tag{1.7}\\
D_{i} & i>j
\end{array}\right.
$$

We denote

$$
\mathcal{P}_{k}(m)=\{0, \ldots, m\}^{k}=\left\{\left(j_{1}, \ldots, j_{k}\right): 0 \leq j_{i} \leq m\right\} .
$$

For any $J \in \mathcal{P}_{k}(m)$ set

$$
q_{J}=\prod_{j \in J} q_{j} \quad \text { and } \quad \chi_{i}(J)=\prod_{j \in J} \chi_{i}(j)
$$

Assume that at time $0 \leq k \leq n-1$, the prices $S_{0}(k), \ldots, S_{i}(m)$ are known. Define for any $0 \leq j \leq m$

$$
\begin{equation*}
Y_{j}(k)=R^{k+1-n} \sum_{J \in \mathcal{P}_{n-k-1}(m)} q_{J}\left(\sum_{i=0}^{m} \gamma_{i} \chi_{i}(J) \chi_{i}(j) S_{i}(k)-K\right)^{+} \tag{1.8}
\end{equation*}
$$

Finally, define the following $(m+1) \times(m+1)$ matrices

$$
\begin{aligned}
& Q=\left[\begin{array}{ccclcc}
1 & 0 & 0 & \cdots \cdots & 0 & 0 \\
-1 & 1 & 0 & \cdots \cdots & 0 & 0 \\
0 & -1 & 1 & \cdots \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \cdots \cdots & & \vdots \\
0 & 0 & 0 & \cdots \cdots & 1 & 0 \\
0 & 0 & 0 & \cdots \cdots & -1 & 1
\end{array}\right] \\
& N=\left[\begin{array}{c|cccc}
1 & D_{1} & D_{2} & \cdots & D_{m} \\
\hline 0 & U_{1}-D_{1} & 0 & \cdots & 0 \\
0 & 0 & U_{2}-D_{2} & & \\
\vdots & \vdots & & \ddots & \vdots \\
0 & 0 & \cdots & & U_{m}-D_{m}
\end{array}\right] \\
& T=\left[\begin{array}{llll}
R S_{0}(k) & & & \\
& S_{1}(k) & & \\
& & \ddots & \\
& & & S_{m}(k)
\end{array}\right]
\end{aligned}
$$

Observe that the matrix $N$ only depend on the parameters of the model, and is easily seen to be invertible. Only the matrix $T$ depends on the state of the world at time $k$, and since $S_{i}(k)>0$ it is clearly invertible. Also, $Q$ is invertible.

Theorem 1.1. With the set up and notation above, at time $0 \leq k \leq n-1$ the portfolio $V_{\alpha}(k)=\sum_{i=0}^{m} \alpha_{i}(k) \cdot S_{i}(k)$ of a minimum cost maximal hedge (1.2), (1.3) for a European contingent claim $X$ in (1.1) is given by

$$
\left[\begin{array}{c}
\alpha_{0}(k) \\
\alpha_{1}(k) \\
\vdots \\
\alpha_{m}(k)
\end{array}\right]=T^{-1} \cdot N^{-1} \cdot Q \cdot\left[\begin{array}{c}
Y_{0}(k) \\
Y_{1}(k) \\
\vdots \\
Y_{m}(k)
\end{array}\right]
$$

Moreover, $V_{\alpha}(k)=C_{\max }(F, k)$.
REMARK: The formula given for $Y_{j}(k)$ has computational complexity $O\left((m+1)^{n-k}\right)$ (the number of terms in the sum). This is exponential in $n$. As discussed in [1], the action of the symmetric group $S_{n-k-1}$ on $\mathcal{P}_{n-k-1}(m)$ gives a formula for $Y_{j}(k)$ whose complexity is only $O\left((n-k)^{m+1}\right)$, polynomial in $n$.
REMARK: As is the case in [1], the function $h(x)=x^{+}$can be replaced with any convex function. Thus, our results apply to several contingent claims other than European basket call options. The reader is referred to [1] for details.

## 2. Formalisation of the model and proof of the main result

2.1. Single time-step. Each step of the model consists of flipping $m$ coins. A natural sample space for this experiment is the set

$$
\underset{3}{\mathcal{L}}=\underset{3}{\{0,1\}^{m}}
$$

of all the sequences of length $m$ consisting of 0's and 1's. We denote its elements by $\lambda=$ $(\lambda(1), \ldots, \lambda(m))$ and view $\mathcal{L}$ as a subset of $\mathbb{R}^{m}$. Let $\ell_{i}$ denote the (random variable of the) result of the $i$-th coin, namely $\ell_{i}: \mathcal{L} \rightarrow \mathbb{R}$ is the projection to the $i$-th factor:

$$
\ell_{i}: \lambda \mapsto \lambda(i)
$$

Observe that $\ell_{i}$ is the restriction to $\mathcal{L}$ of the linear projection function $\pi_{i}: \mathbb{R}^{m} \rightarrow \mathbb{R}$.
Let $\psi_{i}$ be the "price jump" of the $i$-th security. One checks that $\psi_{0}=R$ and that $\psi_{i}(\lambda)=$ $D_{i}+\left(U_{i}-D_{i}\right) \lambda(i)$ for $1 \leq i \leq m$, namely

$$
\begin{equation*}
\psi_{0}=R \quad \text { and } \quad \psi_{i}=D_{i}+\left(U_{i}-D_{i}\right) \ell_{i} \tag{2.1}
\end{equation*}
$$

Thus, for every $1 \leq i \leq m, \psi_{i}$ is the restriction to $\mathcal{L}$ of an affine function $f_{i}: \mathbb{R}^{m} \rightarrow \mathbb{R}$ where $f_{i}\left(x_{1}, \ldots, x_{m}\right)=D_{i}+\left(U_{i}-D_{i}\right) x_{i}$.

Let us consider probability measures on $\mathcal{L}$ on the $\sigma$-algebra $\wp(\mathcal{L})$ of all the subsets of $\mathcal{L}$. These are equivalent to probability density functions $p: \mathcal{L} \rightarrow \mathbb{R}$ and we will abuse notation and write $p$ for both the density function and the probability measure it induces. The requirement that $p$ is risk-neural in a single-step model is the condition

$$
E_{p}\left(\psi_{i}\right)=R, \quad(1 \leq i \leq m)
$$

By the linearity of the expectation and the definition (1.4), this is equivalent to

$$
E_{p}\left(\ell_{i}\right)=b_{i}
$$

Throughout we assume that $b_{1}, \ldots, b_{m}$ is non-increasing (1.5).
Definition 2.1. Let $P(\mathcal{L}, b)$ denote the set of all probability density functions $p: \mathcal{L} \rightarrow \mathbb{R}$ such that $E_{p}\left(\ell_{i}\right)=b_{i}$ for all $1 \leq i \leq m$.

Define $\rho_{0}, \ldots \rho_{m} \in \mathcal{L}$ as follows

$$
\begin{equation*}
\rho_{j}=(\underbrace{1, \ldots, 1}_{j \text { times }}, 0, \ldots, 0) . \tag{2.2}
\end{equation*}
$$

Thus, $\rho_{j}$ describes the event of a run of $j$ heads followed by a run of $n-j$ tails. Use (1.6) to define a probability density function $q: \mathcal{L} \rightarrow \mathbb{R}$ by

$$
q(\lambda)= \begin{cases}q_{j} & \text { if } \lambda=\rho_{j} \text { for some } 0 \leq j \leq m  \tag{2.3}\\ 0 & \text { otherwise }\end{cases}
$$

We call $q$ the upper supermodular vertex of $P(\mathcal{L}, b)$. Compare with $[1$, Appendix A equation (A.6)] where we denoted $\rho_{j}$ by $\mu_{j}$. One checks, see [1, Appendix A], that indeed $q \in P(\mathcal{L}, b)$. In particular

$$
\begin{equation*}
E_{q}\left(\psi_{i}\right)=D_{i}+\left(U_{i}-D_{i}\right) E_{q}\left(\ell_{i}\right)=D_{i}+\left(U_{i}-D_{i}\right) b_{i}=R . \tag{2.4}
\end{equation*}
$$

There is a canonical bijection of $\mathcal{L}$ with the set $\wp(\{1, \ldots, m\})$. This gives rise to a partial order $\preceq$ on $\mathcal{L}$ induced by the partial order $\subseteq$ on $\wp(\{1, \ldots, m\})$. Thus,

$$
\begin{equation*}
\lambda \preceq \lambda^{\prime} \Longleftrightarrow \operatorname{supp}_{4}(\lambda) \subseteq \operatorname{supp}\left(\lambda^{\prime}\right) \tag{2.5}
\end{equation*}
$$

Union and intersection of sets render $\mathcal{L}$ a lattice with join $\vee$ and meet $\wedge$,

$$
\begin{align*}
& \lambda \vee \lambda^{\prime}=\left(\max \left\{\lambda(1), \lambda^{\prime}(1)\right\}, \ldots, \max \left\{\lambda(m), \lambda^{\prime}(m)\right\}\right)  \tag{2.6}\\
& \lambda \wedge \lambda^{\prime}=\left(\min \left\{\lambda(1), \lambda^{\prime}(1)\right\}, \ldots, \min \left\{\lambda(m), \lambda^{\prime}(m)\right\}\right)
\end{align*}
$$

The concept of submodular functions is originally due to Lovász in [2]. In this note, its variant, supermodular functions [3], is used.

Definition 2.2. A function $f: \mathcal{L} \rightarrow \mathbb{R}$ is called supermodular if for any $\lambda, \lambda^{\prime} \in \mathcal{L}$

$$
f\left(\lambda \vee \lambda^{\prime}\right)+f\left(\lambda \wedge \lambda^{\prime}\right) \geq f(\lambda)+f\left(\lambda^{\prime}\right)
$$

It is called modular if equality holds.
Proposition 2.3. (i) A linear combination with non-negative coefficients of supermodular functions is supermodular.
(ii) Let $g: \mathbb{R}^{m} \rightarrow \mathbb{R}$ be an affine function. Then $\left.g\right|_{\mathcal{L}}$ is modular.
(iii) Let $g: \mathbb{R}^{m} \rightarrow \mathbb{R}$ be an affine function of the form $g\left(x_{1}, \ldots, x_{m}\right)=\sum_{i=1}^{m} a_{i} x_{i}+b$ where $a_{1}, \ldots, a_{m} \geq 0$. If $h: \mathbb{R} \rightarrow \mathbb{R}$ is convex then the restriction of $h \circ g$ to $\mathcal{L}$ is supermodular.

Proof. Part (i) is [3, Proposition 2.2.5(a)]. Part (ii) follows from [3, Theorem 2.2.3] (and is straightforward). Part (iii) follows from [3, Theorem 2.2.6(a)].

The crucial property of the upper supermodlar vertex $q(2.3)$ is given by the following result.
Proposition 2.4 ([1, Theorem A.5(i)]). Let $f: \mathcal{L} \rightarrow \mathbb{R}$ be supermodular. Let $q$ be the upper supermodular vertex in $P(\mathcal{L}, b)$. Then

$$
\sup _{p \in P(\mathcal{L}, b)} E_{p}(f)=\max _{p \in P(\mathcal{L}, b)} E_{p}(f)=E_{q}(f)
$$

2.2. Multi time-step model. For the $n$-step model one performs $n$ iterations (not necessarily independent) of the experiment of flipping $m$ coins. Thus, the natural sample space for an $n$-step discrete time binomial market model is $\mathcal{L}^{n}$. We equip it with the $\sigma$-algebra $\mathcal{F}=\wp\left(\mathcal{L}^{n}\right)$ of all subsets of $\mathcal{L}^{n}$.
The "state of the world" at time $0 \leq k \leq n$ is described by a $k$-tuple $\left(\lambda^{1}, \ldots, \lambda^{k}\right) \in \mathcal{L}^{k}$. Thus, the set of the states of the world at time $k$ is naturally identified with $\mathcal{L}^{k}$. We obtain a partition $\left\{\omega \times \mathcal{L}^{n-k}: \omega \in \mathcal{L}^{k}\right\}$ of $\mathcal{L}^{n}$ which generates a sub- $\sigma$-algebra $\mathcal{F}_{k}$.

The price jump of the $i$-th security at time $1 \leq k \leq n$, where $1 \leq i \leq m$, is the random variable $\Psi_{i}(k): \mathcal{L}^{n} \rightarrow \mathbb{R}$

$$
\Psi_{i}(k):\left(\lambda^{1}, \ldots, \lambda^{n}\right) \mapsto \psi_{i}\left(\lambda^{k}\right) .
$$

Of course, $\Psi_{0}(k): \mathcal{L}^{n} \rightarrow \mathbb{R}$ is the constant function (random variable) with value $R$.
The random process $S_{i}(0), \ldots, S_{i}(n)$ of the prices of the $i$-th security at time $0 \leq k \leq n$ are random variables $S_{i}(k): \mathcal{L}^{n} \rightarrow \mathbb{R}$. Clearly, they are given by

$$
\begin{equation*}
S_{i}(k)=S_{i}(0) \cdot \Psi_{i}(1) \cdots \Psi_{i}(k) \tag{2.7}
\end{equation*}
$$

Where $S_{i}(0)>0$ are constant (the initial prices of the securities at time 0 ). Clearly, the value of $S_{i}(k)$ at $\omega \in \mathcal{L}^{n}$ depend only on the first $k$ entries of $\omega$. Hence, $S_{i}(k)$ are $\mathcal{F}_{k}$-measurable random variables, namely their values only depend on the state of the world at time $k$. We will therefore abuse notation and regard $S_{i}(k)$ as functions with domain $\mathcal{L}^{k}$.

We now fix $\gamma_{0}, \ldots, \gamma_{m}$ where $\gamma_{i} \geq 0$ for all $1 \leq i \leq m$ and fix some $K$ and set

$$
\begin{equation*}
F=\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(n)-K\right)^{+} . \tag{2.8}
\end{equation*}
$$

This random variable is the pay-off of the European contingent claim which is the subject of study of this note.

Recall the elements $\rho_{j} \in \mathcal{L}$ from (2.2). Observe that by definition of $\psi_{i}$ (2.1) and of $\chi_{i}$ (1.7) we have

$$
\begin{equation*}
\psi_{i}\left(\rho_{j}\right)=\chi_{i}(j), \quad(0 \leq i, j \leq m) \tag{2.9}
\end{equation*}
$$

Proposition 2.5. Consider some $\omega=\left(\lambda^{1}, \ldots, \lambda^{k}\right) \in \mathcal{L}^{k}$, a state of the world at time $0 \leq k \leq n$, and some $J=\left(j_{1}, \ldots, j_{n-k}\right) \in \mathcal{P}_{n-k}(m)$. Set $\tau=\left(\rho_{j_{1}}, \ldots, \rho_{j_{n-k}}\right) \in \mathcal{L}^{n-k}$. Then

$$
F(\omega \tau)=\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k)(\omega) \chi_{i}(J)-K\right)^{+}
$$

Proof. By the definition of $S_{i}(n)(2.7)$

$$
\begin{aligned}
F(\omega \tau) & =\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(0) \cdot \prod_{p=1}^{n} \Psi_{i}(p)(\omega \tau)-K\right)^{+}= \\
& \left(\sum_{i=0}^{m} \gamma_{i} S_{i}(0) \cdot \prod_{p=1}^{k} \psi_{i}\left(\lambda^{p}\right) \cdot \prod_{p=k+1}^{n} \psi_{i}\left(\rho_{j_{p}}\right)-K\right)^{+}=\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k)(\omega) \cdot \chi_{i}(J)-K\right)^{+} .
\end{aligned}
$$

For every $0 \leq k \leq n$ we will denote by

$$
C_{\max }(F, k) \quad \text { and } \quad C_{\min }(F, k)
$$

the upper and lower bounds of the rational values of $F$ at time $k$. Of course, these numbers depend only on the state of the world at time $k$, and so $C_{\max / \min }(F, k)$ are $\mathcal{F}_{k}$-measurable random variables (on $\mathcal{L}^{n}$ ).

Proposition 2.6. With the pay-off $F$ (2.8) of European basket call, at time $0 \leq k \leq n$

$$
C_{\max }(F, k)=R^{k-n} \sum_{J \in \mathcal{P}_{n-k}(m)} q_{J}\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k) \chi_{i}(J)-K\right)^{+}
$$

Proof. This is an immediate consequence of [1, Example 7.3 and Section 6A eqns. (6.1) and (6.2)] and Proposition 2.5. We note that in [1] the elements $\rho_{j} \in \mathcal{L}$ are denoted $\mu_{j}$ and $\mathcal{P}_{n-k}(m)$ is denoted $I^{n-k}$.

Notice that $C_{\max }(F, k)$ is an $\mathcal{F}_{k}$ measurable random variable on $\mathcal{L}^{n}$. Hence, it will be convenient to think of it as a function with domain $\mathcal{L}^{k}$.

Proposition 2.7. Consider some $0 \leq k \leq n-1$ and some $\omega \in \mathcal{L}^{k}$ representing the state of the world at time $k$. Then the function $f: \mathcal{L} \rightarrow \mathbb{R}$ defined by

$$
f(\lambda)=C_{\max }(F, k+1)(\omega \lambda)
$$

is supermodular. Moreover, with respect to the upper supermodular vertex (2.3)

$$
E_{q}(f)=R \cdot C_{\max }(F, k)(\omega) .
$$

Proof. It follows from Proposition 2.6 and since $S_{i}(k+1)=S_{i}(k) \cdot \Psi_{i}(k+1)$ that

$$
f(\lambda)=R^{k+1-n} \sum_{J \in \mathcal{P}_{n-k-1}(m)} q_{J}\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k)(\omega) \cdot \psi_{i}(\lambda) \cdot \chi_{i}(J)-K\right)^{+} .
$$

Proposition 2.3(i),(iii) implies that $f$ is supermodular since $h(x)=x^{+}$is convex and since $\psi_{i}=D_{i}+\left(U_{i}-D_{i}\right) \ell_{i}$ is an affine function with non-negative coefficients and since $R>0$ and $\gamma_{i}, S_{i}(k), \chi_{i}(J) \geq 0$ for all $1 \leq i \leq m$. Moreover, by (2.9)

$$
\begin{aligned}
E_{q}(f) & =\sum_{\lambda \in \mathcal{L}} q(\lambda) f(\lambda) \\
& =\sum_{j=0}^{m} q\left(\rho_{j}\right) f\left(\rho_{j}\right) \\
& =\sum_{j=0}^{m} q_{j} \sum_{J \in \mathcal{P}_{n-k-1}(m)} q_{J} R^{k+1-n}\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k)(\omega) \cdot \psi_{i}\left(\rho_{j}\right) \cdot \chi_{i}(J)-K\right)^{+} \\
& =\sum_{j=0}^{m} q_{j} \sum_{J \in \mathcal{P}_{n-k-1}(m)} q_{J} R^{k+1-n}\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k)(\omega) \cdot \chi_{i}(J) \chi_{i}(j)-K\right)^{+} \\
& =R \cdot R^{k-n} \sum_{J \in \mathcal{P}_{n-k}(m)} q_{J}\left(\sum_{i=0}^{m} \gamma_{i} S_{i}(k)(\omega) \cdot \chi_{i}(J)-K\right)^{+} \\
& =R \cdot C_{\max }(F, k)(\omega) .
\end{aligned}
$$

Consider some $0 \leq k \leq n-1$ and recall $Y_{j}(k)$ from (1.8) where $0 \leq j \leq m$. Observe that $Y_{j}(k)$ is a function of the random variables $S_{i}(k)$, so $Y_{j}(k)$ is a random variable (on $\mathcal{L}^{n}$ ) whose values depend only on the state of the world at time $k$, namely $Y_{j}(k)$ is $\mathcal{F}_{k}$-measurable.

Proposition 2.8. For any $0 \leq j \leq m$ and any $\omega=\left(\lambda^{1}, \ldots, \lambda^{k}\right) \in \mathcal{L}^{k}$

$$
C_{\max }(F, k+1)\left(\omega \rho_{j}\right)=Y_{j}(\omega) .
$$

Proof. This follows immediately from Propositions 2.6 and equation (2.9).
Proof of Theorem 1.1. Fix some $0 \leq k \leq n-1$ and some state of the world $\omega=\left(\lambda^{1}, \ldots, \lambda^{k}\right) \in$ $\mathcal{L}^{k}$ at time $k$. Any subsequent state of the world at time $k+1$ has the form $\omega \lambda$ for $\lambda \in \mathcal{L}$. Our goal is to find numbers $\alpha_{0}(k)(\omega), \ldots, \alpha_{m}(k)(\omega)$, which for simplicity we denote by $\alpha_{0}, \ldots, \alpha_{m}$, which fulfil the inequality (1.3), namely for every $\lambda \in \mathcal{L}$

$$
\sum_{i=0}^{m} \alpha_{i} S_{i}(k+1)(\omega \lambda) \geq C_{\max }(F, k+1)(\omega \lambda)
$$

and which minimize

$$
\begin{equation*}
V_{\alpha}(k)(\omega)=\sum_{i=0}^{m} \alpha_{i} S_{i}(k)(\omega) . \tag{2.10}
\end{equation*}
$$

We rewrite the first inequality as a set of inequalities (indexed by $\lambda \in \mathcal{L}$ )

$$
\begin{equation*}
\underbrace{\sum_{i=0}^{m} \alpha_{i} S_{i}(k)(\omega) \cdot \psi_{i}(\lambda)}_{\Phi_{\alpha}(\lambda)} \geq \underbrace{C_{\max }(F, k+1)(\omega \lambda)}_{\Xi(\lambda)} \quad(\lambda \in \mathcal{L}) . \tag{2.11}
\end{equation*}
$$

We obtain two functions $\Phi_{\alpha}: \mathcal{L} \rightarrow \mathbb{R}$ and $\Xi: \mathcal{L} \rightarrow \mathbb{R}$, and (2.11) is the inequality

$$
\Phi_{\alpha} \geq \Xi
$$

The first step of the proof is to show that the following system of $m+1$ linear equations with the $m+1$ unknowns $\alpha_{0}, \ldots, \alpha_{m}$ has a unique solution

$$
\sum_{i=0}^{m} \alpha_{i} S_{i}(k)(\omega) \cdot \psi_{i}\left(\rho_{j}\right)=C_{\max }(F, k+1)\left(\omega \rho_{j}\right), \quad(0 \leq j \leq m)
$$

Notice that these equations are obtained by imposing equalities in the inequalities (2.11) for $\lambda=\rho_{0}, \ldots, \rho_{m}$. By (2.9) and by Proposition 2.8, this is the system of equations

$$
\begin{equation*}
\sum_{i=0}^{m} \alpha_{i} S_{i}(k)(\omega) \cdot \chi_{i}(j)=Y_{j}(\omega), \quad(0 \leq j \leq m) \tag{2.12}
\end{equation*}
$$

Write $\alpha_{\bullet}$ for the column vector $\left(\alpha_{0}, \ldots, \alpha_{m}\right)$ and $Y_{\bullet}$ for the column vector $\left(Y_{0}(\omega), \ldots, Y_{m}(\omega)\right)$. Then this system of $m+1$ linear equations is $M \alpha_{\bullet}=Y_{\bullet}$ where $M$ is the $(m+1) \times(m+1)$ matrix

$$
\begin{aligned}
&\left(M_{j, i}\right)=\left(S_{i}(k)(\omega) \cdot \chi_{i}(j)\right)= \\
& \underbrace{\left[\begin{array}{cccc}
1 & \chi_{1}(0) & \cdots & \chi_{m}(0) \\
1 & \chi_{1}(1) & \cdots & \chi_{m}(1) \\
\vdots & \vdots & & \vdots \\
1 & \chi_{1}(m) & \cdots & \chi_{m}(m)
\end{array}\right]}_{M^{\prime}} \cdot \underbrace{\left[\begin{array}{llll}
R S_{0}(k)(\omega) & & & \\
& S_{1}(k)(\omega) & & \\
& & \ddots & \\
& & & S_{m}(k)(\omega)
\end{array}\right]}_{T} .
\end{aligned}
$$

Clearly, $T$ is invertible since $R, S_{i}(k)(\omega)>0$. Observe that for any $1 \leq j \leq m$ and any $0 \leq i \leq m-1$

$$
\chi_{j}(i)-\chi_{j}(i+1)= \begin{cases}0 & i \neq j \\ U_{i}-D_{i} & i=j\end{cases}
$$

By inspection we get

$$
Q \cdot M^{\prime}=\underbrace{\left[\begin{array}{c|cccc}
1 & D_{1} & D_{2} & \cdots & D_{m} \\
\hline 0 & U_{1}-D_{1} & 0 & \cdots & 0 \\
0 & 0 & U_{2}-D_{2} & \cdots & 0 \\
\vdots & & & \ddots & \\
0 & 0 & 0 & \cdots & U_{m}-D_{m}
\end{array}\right]}_{N} .
$$

Clearly, $Q$ and $N$ are invertible, hence so is $M^{\prime}$. It follows that $M=M^{\prime} T$ is invertible, so the system (2.12) has a unique solution given by

$$
\alpha_{\bullet}=T^{-1} N^{-1} Q \cdot Y_{\bullet} .
$$

This gives the values of $\alpha_{i}(k)(\omega)$ stated in the theorem. It remains to show that these $\alpha_{i}$ solve all the inequalities in (2.11) (one for each $\lambda \in \mathcal{L}$ ) and minimize (2.10) and $V_{\alpha}(k)(\omega)=$ $C_{\text {max }}(F, k)(\omega)$.

Claim 1: $\alpha_{0}, \ldots, \alpha_{m}$ solve the inequalities (2.11).
Proof: Suppose that not all these inequalities are solved, namely $\Phi_{\alpha}(\lambda)>\Xi(\lambda)$ for some $\lambda \in \mathcal{L}$. Since $\alpha_{0}, \ldots, \alpha_{m}$ solve the equations (2.12), we certainly get $\Phi_{\alpha}\left(\rho_{i}\right)=\Xi\left(\rho_{i}\right)$ for all $0 \leq i \leq m$.

Among all $\lambda \in \mathcal{L}$ for which $\Phi(\lambda)>\Xi(\lambda)$ choose one with maximal possible $j$ such that $\rho_{j} \preceq \lambda(2.5)$. Observe that $j<m$ because if $j=m$ then $\rho_{m} \preceq \lambda$ implies that $\lambda=\rho_{m}$ which we have seen is impossible. Set $\lambda^{\prime}=\lambda \vee \rho_{j+1}$ (2.6). By the maximality of $j$ we get that $\lambda \wedge \rho_{j+1}=\rho_{j}$. Observe that $\Phi_{\alpha}$ is an affine function, hence it is modular by Proposition 2.3(ii), so

$$
\Phi\left(\lambda^{\prime}\right)+\Phi\left(\rho_{j}\right)=\Phi(\lambda)+\Phi\left(\rho_{j+1}\right)
$$

By Proposition $2.7 \Xi$ is supermodular, so

$$
\Xi\left(\lambda^{\prime}\right)+\Xi\left(\rho_{j}\right) \geq \Xi(\lambda)+\Xi\left(\rho_{j+1}\right)
$$

Subtracting the first equality from the second inequality, and recalling that $\Phi\left(\rho_{i}\right)=\Xi\left(\rho_{i}\right)$ for all $i$, we get

$$
\Xi\left(\lambda^{\prime}\right)-\Phi\left(\lambda^{\prime}\right) \geq \Xi(\lambda)-\Psi(\lambda)>0
$$

So $\Phi\left(\lambda^{\prime}\right)>\Xi\left(\lambda^{\prime}\right)$ and $\rho_{j+1} \preceq \lambda^{\prime}$ which contradicts the maximality of $j$.
Recall that any $\beta_{0}, \ldots, \beta_{m}$ define $V_{\beta}(k)(\omega)$ in (2.10).
Claim 2: For any $\beta_{0}, \ldots, \beta_{m}$ for which the inequalities (2.11) hold,

$$
V_{\beta}(k)(\omega) \geq C_{\max }(F, k)(\omega)
$$

In addition, $\alpha_{0}, \ldots, \alpha_{m}$ attain this lower bound, namely

$$
V_{\alpha}(k)(\omega)=C_{9}^{\max ^{2}}(F, k)(\omega) .
$$

Proof: Suppose $\beta_{i}$ solve the inequalities (2.11). It follows from (2.4) that

$$
\begin{equation*}
E_{q}\left(\Phi_{\beta}\right)=\sum_{i=0}^{m} \beta_{i} S_{i}(k)(\omega) \cdot E_{q}\left(\psi_{i}\right)=R \cdot \sum_{i=0}^{m} \beta_{i} S_{i}(k)(\omega)=R V_{\beta}(k)(\omega) . \tag{2.13}
\end{equation*}
$$

Proposition 2.7 implies that $E_{q}(\Xi)=R C_{\max }(F, k)(\omega)$. Since $\beta_{i}$ solve the inequalities (2.11), this means $\Phi_{\beta} \geq \Xi$. By the monotonicity of the expectation, $E_{q}\left(\Phi_{\beta}\right) \geq E_{q}(\Xi)$, and since $R>0$, it follows that $V_{\beta}(k)(\omega) \geq C_{\max }(F, k)(\omega)$ as needed.
By construction $\Phi_{\alpha}\left(\rho_{j}\right)=\Xi\left(\rho_{j}\right)$ for all $j=0, \ldots, m$. Since $q$ is supported on $\rho_{0}, \ldots, \rho_{m}$, we deduce from (2.13) that

$$
R V_{\alpha}(k)(\omega)=E_{q}\left(\Phi_{\alpha}\right)=E_{q}(\Xi)=R \cdot C_{\max }(F, k)(\omega) .
$$

Hence $V_{\alpha}(k)(\omega)=C_{\max }(F, k)(\omega)$.
q.e.d

The theorem follows from Claims 1 and 2.

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