Arbitrage-Free Pricing Models

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Option Pricing by Replication

- The original approach to option pricing, going back to Black, Scholes, and Merton, is to use a replication argument together with the Law of One Price.
- Consider a binomial model for the stock price



- Payoff of any option on the stock can be replicated by dynamic trading in the stock and the bond, thus there is a unique arbitrage-free option valuation.
- Problem solved?

Drawbacks of the Binomial Model

- The binomial model (and its variants) has a few issues.
- If the binomial depiction of market dynamics was accurate, all options would be redundant instruments. Is that realistic?
- Empirically, the model has problems: one should be able to replicate option payoffs perfectly in theory, that does not happen in reality.
- Why build models like the binomial model? Convenience. Unique option price by replication is a very appealing feature.
- How can one make the model more realistic, taking into account lack of perfect replication?

Futures

Arbitrage and Option Pricing



Arbitrage and Option Pricing

- Take an alternative approach to option pricing.
- Even when options cannot be replicated (options are not redundant), there should be no arbitrage in the market.
- The problem with non-redundant options is that there may be more than one value of the option price today consistent with no arbitrage.
- Change the objective: construct a tractable joint model of the primitive assets (stock, bond, etc.) and the options, which is
 - Free of arbitrage;
 - Conforms to empirical observations.
- When options are redundant, no need to look at option price data: there is a unique option price consistent with no arbitrage.
- When options are non-redundant, there may be many arbitrage-free option prices at each point in time, so we need to rely on historical option price data to help select among them.
- We know how to estimate dynamic models (MLE, QMLE, etc.). Need to learn how to build tractable arbitrage-free models.

Absence of Arbitrage

- Consider a finite-horizon discrete-time economy, time = {0, ..., T}.
- Assume a finite number of possible states of nature, s = 1, ..., N



Definition (Arbitrage)

Arbitrage is a feasible cash flow (generated by a trading strategy) which is non-negative in every state and positive with non-zero probability.

Absence of Arbitrage

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Arbitrage is a feasible cash flow (generated by a trading strategy) which is non-negative in every state and positive with non-zero probability.

- We often describe arbitrage as a strategy with no initial investment, no risk of a loss, and positive expected profit. It's a special case of the above definition.
- Absence of arbitrage implies the Law of One Price: two assets with the same payoff must have the same market price.
- Absence of arbitrage may be a very weak requirement in some settings and quite strong in others:
 - Equities: few securities, many states. Easy to avoid arbitrage.
 - Fixed income: many securities, few states. Not easy to avoid arbitrage.

Risk-Neutral Pricing

Absence of Arbitrage

Fundamental Theorem of Asset Pricing (FTAP)

Proposition (FTAP)

Absence of arbitrage is equivalent to existence of a positive stochastic process $\{\pi_t(s) > 0\}$ such that for any asset with price P_t ($P_T = 0$) and cash flow D_t ,

$$P_t(s) = E_t \left[\sum_{u=t+1}^T \frac{\pi_u(s)}{\pi_t(s)} D_u(s) \right]$$

or, in return form,

$$E_t\left[\frac{\pi_{t+1}(s)}{\pi_t(s)}R_{t+1}(s)\right] = 1, \quad R_{t+1}(s) = \frac{P_{t+1}(s) + D_{t+1}(s)}{P_t(s)}$$

- Stochastic process $\pi_t(s)$ is also called the state-price density (SPD).
- FTAP implies the Law of One Price.

- Prove one direction (the easier one): if SPD exists, there can be no arbitrage.
- Let W_t denote the portfolio value, $(\theta^1, ..., \theta^N)$ are holdings of risky assets 1, ..., N.
- Manage the portfolio between t = 0 and t = T.
- An arbitrage is a strategy such that $W_0 \leq 0$ while $W_T \geq 0$, $W_T \neq 0$.
- The trading strategy is self-financing if it does not generate any cash in- or out-flows except for time 0 and *T*.
- Formal self-financing condition

$$W_{t+1} = \sum_{i} \theta_{t+1}^{i} P_{t+1}^{i} = \sum_{i} \theta_{t}^{i} (P_{t+1}^{i} + D_{t+1}^{i})$$

Future

Absence of Arbitrage

From SPD to No Arbitrage

• Show that self-financing implies that $\pi_t W_t = E_t[\pi_{t+1} W_{t+1}]$:

$$\mathsf{E}_{t}[\pi_{t+1} \mathsf{W}_{t+1}] = \mathsf{E}_{t}[\pi_{t+1} \sum_{i} \theta_{t+1}^{i} \mathsf{P}_{t+1}^{i}] \stackrel{\text{self financing}}{=} \mathsf{E}_{t} \left[\pi_{t+1} \sum_{i} \theta_{t}^{i} (\mathsf{P}_{t+1}^{i} + \mathsf{D}_{t+1}^{i}) \right]$$

$$\stackrel{\text{FTAP}}{=} \sum_{i} \theta_{t}^{i} \pi_{t} \mathsf{P}_{t}^{i} = \pi_{t} \mathsf{W}_{t}$$

• Start at 0 and iterate forward

$$\begin{aligned} \pi_0 \, W_0 &= \mathsf{E}_0[\pi_1 \, W_1] = \mathsf{E}_0[\mathsf{E}_1[\pi_2 \, W_2]] \\ &= \mathsf{E}_0[\pi_2 \, W_2] = \dots \\ &= \mathsf{E}_0[\pi_T \, W_T] \end{aligned}$$

• Given that the SPD is positive, it is impossible to have $W_0 \leq 0$ while $W_T \geq 0$, $W_T \neq 0$. Thus, there can be no arbitrage.

Absence of Arbitrage

Fundamental Theorem of Asset Pricing (FTAP)

• When there exists a full set of state-contingent claims (markets are complete), there is a unique SPD consistent with absence of arbitrage:

 $\pi_t(s)$ is the price of a state-contingent claim paying \$1 in state *s* at time *t*, normalized by the probability of that state, p_t .

- The reverse is also true: if there exists only one SPD, all options are redundant.
- When there are fewer assets than states of nature, there can be many SPDs consistent with no arbitrage.
- FTAP says that if there is no arbitrage, there must be at least one way to introduce a consistent system of positive state prices.
- We drop explicit state-dependence and write π_t instead of $\pi_t(s)$.

Example: Binomial Tree

- Options are redundant: any payoff can be replicated by dynamic trading.
- FTAP implies that

 $\pi_0 = 1$:

$$\begin{array}{lll} \frac{\pi_{t+1}(u)}{\pi_t} & = & \frac{1}{p(1+r)} \frac{1+r-d}{u-d} \\ \frac{\pi_{t+1}(d)}{\pi_t} & = & \frac{1}{(1-p)(1+r)} \frac{u-(1+r)}{u-d} \end{array}$$

Arbitrage-Free Models using SPD

Discounted Cash Flow Model (DCF)

Algorithm: A DCF Model

- Specify the process for cash flows, D_t.
- 3 Specify the SPD, π_t .
- Oerive the asset price process as

$$P_t = \mathsf{E}_t \left[\sum_{u=t+1}^T \frac{\pi_u}{\pi_t} D_u \right] \tag{DCF}$$

- To make this practical, need to learn how to parameterize SPDs in step (2), so that step (3) can be performed efficiently.
- Can use discrete-time conditionally Gaussian processes.
- SPDs are closely related to risk-neutral pricing measures. Useful for building intuition and for computations.

SPD and the Risk Premium

• Let *R*_{t+1} be the gross return on a risky asset between *t* and *t* + 1:

$$\mathsf{E}_{t}\left[\frac{\pi_{t+1}}{\pi_{t}}R_{t+1}\right] = \mathsf{1}$$
$$\mathsf{E}_{t}\left[\frac{\pi_{t+1}}{\pi_{t}}(\mathsf{1}+r_{t})\right] = \mathsf{1}$$

• Using the definition of covariance,

Conditional Risk Premium and SPD Beta

Risk Premium_t
$$\equiv \mathsf{E}_t[R_{t+1}] - (1 + r_t) = -(1 + r_t)\mathsf{Cov}_t\left(R_{t+1}, \frac{\pi_{t+1}}{\pi_t}\right)$$

SPD and CAPM

- CAPM says that risk premia on all stocks must be proportional to their market betas.
- CAPM can be re-interpreted as a statement about the SPD pricing all assets.
- Assume that

$$\pi_{t+1}/\pi_t = a - bR_{t+1}^M$$

where R^{M} is the return on the market portfolio. (The above formula may be viewed as approximation, if it implies negative values of π).

• Using the general formula for the risk premium, for any stock *j*,

$$\mathsf{E}_{t}\left[\boldsymbol{R}_{t+1}^{j}-(1+r_{t})\right]=const\times\mathsf{Cov}_{t}(\boldsymbol{R}_{t+1}^{j},\boldsymbol{R}_{t+1}^{M})$$

• The above formula works for any asset, including the market return. Use this to find the constant:

$$\mathsf{E}_{t}\left[R_{t+1}^{j} - (1+r_{t})\right] = \mathsf{E}_{t}\left[R_{t+1}^{M} - (1+r_{t})\right] \frac{\mathsf{Cov}_{t}(R_{t+1}^{j}, R_{t+1}^{M})}{\mathsf{Var}_{t}(R_{t+1}^{M})}$$

SPD and Multi-Factor Models

- Alternative theories (e.g., APT), imply that there are multiple priced factors in returns, not just the market factor.
- Multi-factor models are commonly used to describe the cross-section of stock returns (e.g., the Fama-French 3-factor model).
- Assume that

$$\pi_{t+1}/\pi_t = a + b_1 F_{t+1}^1 + \dots b_K F_{t+1}^K$$

where F^k , k = 1, ..., K are K factors. Factors may be portfolio returns, or non-return variables (e.g., macro shocks).

Then risk premia on all stocks have factor structure

$$\mathsf{E}_{t}\left[\boldsymbol{R}_{t+1}^{j}-(1+\boldsymbol{r}_{t})\right]=\sum_{k=1}^{K}\lambda_{k}\mathsf{Cov}_{t}\left(\boldsymbol{R}_{t+1}^{j},\boldsymbol{F}_{t+1}^{k}\right)$$

• Factor models are simply statements about the factor structure of the SPD.

Futures

SPDs and Risk-Neutral Pricing

- One can build models by specifying the SPD and computing all asset prices.
- It is typically more convenient to use a related construction, called risk-neutral pricing.
- Risk-neutral pricing is a mathematical construction. It is often convenient and adds something to our intuition.

Risk-Neutral Measures

- The DCF formulation with an SPD is mathematically equivalent to a change of measure from the physical probability measure to the risk-neutral measure. The risk-neutral formulation offers a useful and tractable alternative to the DCF model.
- Let **P** denote the physical probability measure (the one behind empirical observations), and **Q** denote the risk-neutral measure. **Q** is a mathematical construction used for pricing and only indirectly connected to empirical data.
- Let *B_t* denote the value of the risk-free account:

$$B_t = \prod_{u=0}^{t-1} (1+r_u)$$

where r_u is the risk-free rate during the period [u, u + 1).

• Q is a probability measure under which

$$P_t = \mathsf{E}_t^{\mathsf{P}} \left[\sum_{u=t+1}^T \frac{\pi_u}{\pi_t} D_u \right] = \mathsf{E}_t^{\mathsf{Q}} \left[\sum_{u=t+1}^T \frac{B_t}{B_u} D_u \right], \quad \text{for any asset with cash flow } D$$

Risk-Neutral Pricing

- Under **Q**, the standard DCF formula holds.
- Under **Q**, expected returns on all assets are equal to the risk-free rate:

$$\mathsf{E}^{\mathbf{Q}}_{t}\left[\boldsymbol{R}_{t+1}\right] = 1 + r_{t}$$

- If **Q** has positive density with respect to **P**, there is no arbitrage.
- There may exist multiple risk-neutral measures.
- **Q** is also called an equivalent martingale measure (EMM).

SPD and Change of Measure

- Construct risk-neutral probabilities from the SPD.
- Consider our tree-model of the market and let C(ν_t) denote the set of time-(t + 1) nodes which are children of node ν_t.
- Define numbers $q(v_{t+1})$ for all nodes $v_{t+1} \in \mathbb{C}(v_t)$ by the formula

$$q(v_{t+1}) = (1 + r_t)q(v_t)\frac{\pi(v_{t+1})p(v_{t+1})}{\pi(v_t)p(v_t)}$$

- Recall that the ratio $p(v_{t+1})/p(v_t)$ is the node- v_t conditional probability of v_{t+1} .
- $q(v_{t+1}) > 0$ and

$$\sum_{\mathbf{v}_{t+1} \in \mathcal{C}(\mathbf{v}_t)} q(\mathbf{v}_{t+1}) = q(\mathbf{v}_t) \sum_{\mathbf{v}_{t+1} \in \mathcal{C}(\mathbf{v}_t)} (1+r_t) \frac{\pi(\mathbf{v}_{t+1}) p(\mathbf{v}_{t+1})}{\pi(\mathbf{v}_t) p(\mathbf{v}_t)}$$
$$= q(\mathbf{v}_t) \mathbf{E}_t^{\mathbf{P}} \left[\frac{\pi(\mathbf{v}_{t+1})}{\pi(\mathbf{v}_t)} (1+r_t) \right] = q(\mathbf{v}_t)$$

SPD and Change of Measure

- $q(v_t)$ define probabilities. Are these risk-neutral probabilities?
- For any asset *i*,

$$\mathsf{E}_{t}^{\mathsf{Q}} \left[\frac{1}{1+r_{t}} R_{t+1}^{i} \right] = \sum_{\mathbf{v}_{t+1} \in \mathcal{C}(\mathbf{v}_{t})} \frac{q(\mathbf{v}_{t+1})}{q(\mathbf{v}_{t})} \frac{1}{1+r_{t}} R_{t+1}^{i}$$

$$= \sum_{\mathbf{v}_{t+1} \in \mathcal{C}(\mathbf{v}_{t})} (1+r_{t}) \frac{\pi(\mathbf{v}_{t+1}) p(\mathbf{v}_{t+1})}{\pi(\mathbf{v}_{t}) p(\mathbf{v}_{t})} \frac{1}{1+r_{t}} R_{t+1}^{i}$$

$$= \sum_{\mathbf{v}_{t+1} \in \mathcal{C}(\mathbf{v}_{t})} \frac{p(\mathbf{v}_{t+1})}{p(\mathbf{v}_{t})} \frac{\pi(\mathbf{v}_{t+1})}{\pi(\mathbf{v}_{t})} R_{t+1}^{i}$$

$$= \mathsf{E}_{t}^{\mathsf{P}} \left[\frac{\pi_{t+1}}{\pi_{t}} R_{t+1}^{i} \right] = 1$$

• Conclude that $q(v_t)$ define risk-neutral probabilities.

Example: Binomial Tree

Risk-Neutral Measure

FTAP implies that

$$qu+(1-q)d = 1+r_t \Rightarrow q = \frac{1+r-d}{u-d}$$

 Alternatively, compute transition probability under **Q** using the SPD π:

$$q = p(1 + r_t) \frac{\pi_{t+1}(u)}{\pi_t}$$

= $p(1 + r_t) \frac{1}{p(1 + r_t)} \frac{1 + r_t - d}{u - d} = \frac{1 + r_t - d}{u - d}$



Normality-Preserving Change of Measure Results

- Under P, $\epsilon^{P} \sim \mathcal{N}(0, 1)$. Define a new measure Q, such that under Q, $\epsilon^{P} \sim \mathcal{N}(-\eta, 1)$.
- Let $\xi = \frac{d\mathbf{Q}}{d\mathbf{P}}$. Then,

$$\xi(\epsilon^{\textbf{P}}) = \text{exp}\left(-\frac{(\epsilon^{\textbf{P}}+\eta)^2}{2} + \frac{(\epsilon^{\textbf{P}})^2}{2}\right) = \text{exp}\left(-\eta\epsilon^{\textbf{P}} - \frac{\eta^2}{2}\right)$$

The change of measure is given by a log-normal random variable $\xi(\varepsilon^{\mathbf{P}})$ serving as the density of the new measure.

Normality-Preserving Change of Measure

$$rac{d\mathbf{Q}}{d\mathbf{P}} = e^{-\eta \, \varepsilon^{\mathbf{P}} - \eta^2/2} \Rightarrow \varepsilon^{\mathbf{Q}} = \varepsilon^{\mathbf{P}} + \eta \sim \mathcal{N}(\mathbf{0}, \mathbf{1}) ext{ under } \mathbf{Q}$$

Price of Risk

- When **P** and **Q** are both Gaussian, we can define the *price of risk* (key notion in continuous-time models).
- Consider an asset with gross return

$$R_{t+1} = \exp\left(\mu_t - \sigma_t^2/2 + \sigma_t \varepsilon_{t+1}^{\mathbf{P}}\right)$$
, $E_t[R_{t+1}] = \exp(\mu_t)$

where $\boldsymbol{\epsilon}_{t+1}^{\textbf{P}} \sim \mathcal{N}(\textbf{0},\textbf{1}),$ IID, under the physical P-measure.

• Let the short-term risk-free interest rate be

$$\exp(r_t) - 1$$

Let the SPD be

$$\pi_{t+1} = \pi_t \exp\left(-r_t - \eta_t^2/2 - \eta_t \varepsilon_{t+1}^{\mathbf{P}}\right)$$

Recall

$$\varepsilon_t^{\mathbf{Q}} = \varepsilon_t^{\mathbf{P}} + \eta_t$$

• Under **Q**, the return distribution becomes

$$\textit{\textit{R}}_{t+1} = \exp\left(\mu_t - \sigma_t^2/2 - \sigma_t\eta_t + \sigma_t \varepsilon_{t+1}^{\textbf{Q}}\right)$$

where $\varepsilon_{t+1}^{\mathbf{Q}} \sim \mathcal{N}(0, 1)$, IID, under the **Q**-measure.

• Under **Q**,

$$\mathbf{R}_{t+1} = \exp\left(\mu_t - \sigma_t^2/2 - \sigma_t \eta_t + \sigma_t \varepsilon_{t+1}^{\mathbf{Q}}\right), \quad \varepsilon_{t+1}^{\mathbf{Q}} \sim \mathcal{N}(\mathbf{0}, \mathbf{1})$$

• By definition of the risk-neutral probability measure,

$$\mathsf{E}^{\mathbf{Q}}_{t}[\mathbf{R}_{t+1}] = \exp(\mathbf{r}_{t}) \quad \Rightarrow \quad \mu_{t} - \sigma_{t}\eta_{t} = \mathbf{r}_{t}$$

• The risk premium (measured using log expected gross returns) equals

$$\mu_t - r_t = \sigma_t \eta_t$$

 σ_t is the quantity of risk, η_t is the price of risk.

• Models with time-varying price of risk, η_t , exhibit return predictability.

			Option Pricing	
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- As an example of how risk-neutral pricing is used, we consider the problem of option pricing when the underlying asset exhibits stochastic volatility.
- The benchmark model is the Black-Scholes model.
- Stock (underlying) volatility in the B-S model is constant.
- Empirically, the B-S model is rejected: the implied volatility is not the same for options with different strikes.
- There are many popular generalizations of the B-S model. We explore the model with an EGARCH volatility process.
- The EGARCH model addresses some of the empirical limitations of the B-S model.

Futures

The Black-Scholes Model

• Consider a stock with price S_t , no dividends. Assume that

$$rac{S_{t+1}}{S_t} = \exp\left(\mu - \sigma^2/2 + \sigma arepsilon_{t+1}^{\mathbf{P}}
ight)$$
 ,

where $\boldsymbol{\epsilon}_{t+1}^{\textbf{P}} \sim \mathcal{N}(\textbf{0},\textbf{1}),$ IID, under the physical P-measure.

- Assume that the short-term interest rate is constant.
- Assume that under the Q-measure,

$$\frac{S_{t+1}}{S_t} = \exp\left(r - \sigma^2/2 + \sigma \varepsilon_{t+1}^{\mathbf{Q}}\right), \quad \varepsilon_{t+1}^{\mathbf{Q}} \sim \mathcal{N}(0, 1), \text{ IID}$$

The time-t price of *any* European option on the stock, with a payoff C_T = H(S_T), is given by

$$C_t = \mathsf{E}_t^{\mathsf{Q}} \left[e^{-r(T-t)} H(S_T) \right]$$

• This is an arbitrage-free model. Prices of European call and put options are given by the Black-Scholes formula.

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- The Black-Scholes model expresses the price of the option as a function of the parameters and the current stock price.
- European Call option price

 $C(S_t, K, r, \sigma, T)$

Implied volatility σ̂_i of a Call option with strike K_i and time to maturity T_i is defined by

$$C_i = C(S_t, K_i, r, \widehat{\sigma}_i, T_i)$$

- Implied volatility reconciles the observed option price with the B-S formula.
- Option prices are typically quoted in terms of implied volatilities.

Introduction

Implied Volatility Smile (Smirk)

- If option prices satisfied the B-S assumptions, all implied volatilities would be the same, equal to σ, the volatility of the underlying price process.
- Empirically, implied volatilities depend on the strike and time to maturity.

FIGURE 2. Implied Volatilities of S&P 500 Options on May 5, 1993



Source: E. Derman, I. Kani, 1994, The Volatility Smile and Its Implied Tree, Quantitative Strategies Research Notes, Goldman Sachs

			Option Pricing	
EGAR	CH Model			

- Consider a model of stock returns with EGARCH volatility process.
- Assume the stock pays no dividends, and short-term interest rate is constant.
- Stock returns are conditionally log-normally distributed under the Q-measure

$$ln \frac{S_t}{S_{t-1}} = r - \frac{\sigma_{t-1}^2}{2} + \sigma_{t-1} \varepsilon_t^{\mathbf{Q}}, \quad \varepsilon_t^{\mathbf{Q}} \sim \mathcal{N}(0, 1), \text{ IID}$$

- Conditional expected gross return on the underlying asset equals exp(r).
- Conditional volatility σ_t follows an EGARCH process under Q

$$\ln\left(\sigma_{t}^{2}\right) = a_{0} + b_{1}\ln\left(\sigma_{t-1}^{2}\right) + \theta\varepsilon_{t-1}^{\mathbf{Q}} + \gamma\left(\left|\varepsilon_{t-1}^{\mathbf{Q}}\right| - \sqrt{\frac{2}{\pi}}\right)$$

• Option prices can be computed using the risk-neutral valuation formula.

- We use Monte Carlo simulation to compute option prices.
- Using the valuation formula

$$C_t = \mathsf{E}_t^{\mathsf{Q}}\left[e^{-r(T-t)}H(\mathcal{S}_T)
ight]$$

Call option price can be estimated by simulating *N* trajectories of the underlying asset S_u^n , n = 1, ..., N, under **Q**, and averaging the discounted payoff

$$C_t \approx \frac{1}{N} \sum_{n=1}^{N} e^{-r(T-t)} \max(S_T^n - K, 0)$$

• Resulting option prices are arbitrage-free because they satisfy the risk-neutral pricing relationship.

			Option Pricing	
Simulat	ion			

- Use one-week time steps.
- Calibrate the parameters using the estimates in Day and Lewis (1992, Table 3)

• Calibrate the interest rate

$$\exp(52 \times r) = \exp(0.05)$$

- Start all *N* trajectories with the same initial stock price and the same initial volatility, $\sigma_0 = 15.5\%/\sqrt{52}$.
- Compute implied volatilities for Call/Put options with different strikes.
- Plot implied volatilities against Black-Scholes deltas of Put options $(\Delta_t = \partial P_t / \partial S_t).$

Volatility Smile



			Futures
Futures			

- We want to build an arbitrage-free model of futures prices.
- In case of deterministic interest rates and costless storage of the underlying asset, futures price is the same as the forward price.
- In most practical situations, storage is not costless, so simple replication arguments are not sufficient to derive futures prices.
- Want to model futures prices for multiple maturities in an arbitrage-free framework.

Risk-Neutral Pricing

- Φ_t^T is the time-*t* futures price for a contract maturing at *T*.
- Futures are continuously settled, so the holder of the long position collects

$$\Phi_t^T - \Phi_{t-1}^T$$

each period. Continuous settlement reduces the likelihood of default.

- The market value of the contract is always equal to zero.
- In the risk-neutral pricing framework

$$\mathsf{E}^{\mathbf{Q}}_{t}\left[\sum_{u=t+1}^{T}\frac{B_{t}}{B_{u}}\left(\Phi_{u}^{T}-\Phi_{u-1}^{T}\right)\right]=0\quad\text{for all }t$$

 We conclude (using backwards induction and iterated expectations) that the futures prices must satisfy

$$\mathbf{E}_{t}^{\mathbf{Q}}\left[\Phi_{t+1}^{T}-\Phi_{t}^{T}\right]=0 \quad \text{for all } t$$

and thus

$$\Phi_t^T = \mathsf{E}_t^{\mathsf{Q}} \left[\Phi_T^T \right] = \mathsf{E}_t^{\mathsf{Q}} \left[\mathcal{S}_T \right]$$

where S_T is the spot price at T.



Suppose that the spot price follows an AR(1) process under the P-measure

$$S_t - \overline{S} = \theta(S_{t-1} - \overline{S}) + \sigma \varepsilon_t^{\mathbf{P}}, \quad \varepsilon_t^{\mathbf{P}} \sim \mathcal{N}(0, 1), \text{ IID}$$

 Assume that the risk-neutral Q-measure is related to the physical P-measure by the state-price density

$$\frac{\pi_{t+1}}{\pi_t} = \exp\left(-r_t - \frac{\eta^2}{2} - \eta \varepsilon_{t+1}^{\mathbf{P}}\right)$$

- Market price of risk η is constant.
- To compute futures prices, use $\varepsilon_t^{\mathbf{Q}} = \varepsilon_t^{\mathbf{P}} + \eta$.



Under the risk-neutral measure, spot price follows

$$S_{t} = \left(\overline{S} - \frac{\eta\sigma}{1 - \theta}\right) + \theta \left[S_{t-1} - \left(\overline{S} - \frac{\eta\sigma}{1 - \theta}\right)\right] + \sigma\varepsilon_{t}^{\mathbf{Q}}$$

Define a new constant

$$\overline{S}^{\mathbf{Q}} \equiv \overline{S} - \frac{\eta \sigma}{1 - \theta}$$

Then

$$S_t - \overline{S}^{\mathbf{Q}} = \theta \left(S_{t-1} - \overline{S}^{\mathbf{Q}} \right) + \sigma \varepsilon_t^{\mathbf{Q}}$$

• Under **Q**, spot price is still AR(1), same mean-reversion rate, but different long-run mean.

AR(1) Spot Price

• To compute the futures price, iterate the AR(1) process forward

$$\begin{split} S_{t+1} - \overline{S}^{\mathbf{Q}} &= \theta \left(S_t - \overline{S}^{\mathbf{Q}} \right) + \sigma \varepsilon_{t+1}^{\mathbf{Q}} \\ S_{t+2} - \overline{S}^{\mathbf{Q}} &= \theta \left(S_{t+1} - \overline{S}^{\mathbf{Q}} \right) + \sigma \varepsilon_{t+2}^{\mathbf{Q}} \\ &= \theta^2 \left(S_t - \overline{S}^{\mathbf{Q}} \right) + \sigma \varepsilon_{t+2}^{\mathbf{Q}} + \theta \sigma \varepsilon_{t+1}^{\mathbf{Q}} \\ &\vdots \\ S_{t+n} - \overline{S}^{\mathbf{Q}} &= \theta^n \left(S_t - \overline{S}^{\mathbf{Q}} \right) + \sigma \varepsilon_{t+n}^{\mathbf{Q}} + \dots + \theta^{n-2} \sigma \varepsilon_{t+2}^{\mathbf{Q}} + \theta^{n-1} \sigma \varepsilon_{t+1}^{\mathbf{Q}} \end{split}$$

We conclude that

$$\Phi_t^{\mathsf{T}} = \mathsf{E}_t^{\mathsf{Q}}\left[S_{\mathsf{T}}\right] = \overline{S}^{\mathsf{Q}}\left(1 - \theta^{\mathsf{T}-t}\right) + \theta^{\mathsf{T}-t}S_t$$

 Futures prices of various maturities given by the above model do not admit arbitrage.

Expected Gain on Futures Positions

- What is the expected gain on a long position in a futures contract?
- Under **Q**, the expected gain is zero:

$$\mathsf{E}^{\mathsf{Q}}_{t}\left[\left(\Phi^{\mathsf{T}}_{t+1}-\Phi^{\mathsf{T}}_{t}
ight)
ight]=\mathsf{0} \quad ext{for all } t$$

• Futures contracts provides exposure to risk, ε^{P} . This risk is compensated, with the market price of risk η .

$$\Phi_{t+1}^{T} - \Phi_{t}^{T} = \sigma \theta^{T-t-1} \varepsilon_{t+1}^{\mathbf{Q}} = \eta \sigma \theta^{T-t-1} + \sigma \theta^{T-t-1} \varepsilon_{t+1}^{\mathbf{P}}$$

(Use $\varepsilon_{t+1}^{\mathbf{Q}} = \eta + \varepsilon_{t+1}^{\mathbf{P}}$)

• Under P, expected gain is non-zero, because ϵ^{Q} has non-zero mean under P

$$\mathsf{E}^{\mathbf{P}}_{t}\left[\left(\Phi^{\mathcal{T}}_{t+1} - \Phi^{\mathcal{T}}_{t}\right)\right] = \eta \sigma \theta^{\mathcal{T}-t-1} \quad \text{for all } t$$

• Can estimate model parameters, including η , from historical futures prices.

			Futures
Summa	ary		

- Existence of SPD or risk-neutral probability measure guarantees absence of arbitrage.
- Factor pricing models, e.g., CAPM, are models of the SPD.
- Can build consistent models of multiple options by specifying the risk-neutral dynamics of the underlying asset.
- Black-Scholes model, volatility smiles, and stochastic volatility models.

			Futures
Readir	ngs		

- Back 2005, Chapter 1.
- E. Derman, I. Kani, 1994, The Volatility Smile and Its Implied Tree, *Quantitative Strategies Research Notes*, Goldman Sachs.
- T. Day, C. Lewis, 1992, Stock Market Volatility and the Information Content of Stock Index Options, *Journal of Econometrics* 52, 267-287.

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