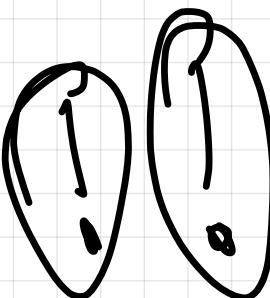



5) Всемирное уравнение

Очевидно

$$Ax + (1-2)y \in C \Rightarrow A2x \in (C, 2)$$



$$2x + (1-2)y \in C$$

$$Ax - b = 0$$

также

$$A(2x + (1-2)y) - b =$$

$$= 2Ax + (1-2)y - 2b - (1-2)b =$$

$$= 0$$

$$2(Ax - b) + (1-2)(Ay - b)$$

$$x^T \nabla R \leq l$$

$$\nabla x > 0$$

$\forall x: x^T \nabla x > 0$

$$(2x + (l-2)e^T)^T (2x + (l-2)e^T) =$$

$$= 2x^2 + (l-2)^2 +$$

$$+ 2x^T e(l-2) - l \leq 0$$

$$+ 2x^T Ax + (l-2)^T A^T e$$

$$(2x + (l-2)e^T)^T (2x + (l-2)e^T) =$$

$$= 2(2-2)(x^T x - 2x^T N e +$$

$$+ e^T V e) + 2x^T N x + (2-2)e^T N e$$

$$2^2 - 2 x^T x$$

$$2^2 - 2 \rightarrow (2-2)^2 = 1-2 + 2 =$$

$$= 1-2 + 2-2 =$$

$$= (2-2) + 2(2-2)$$

$\leftarrow 0$

$$(2x + (2-2)x^T V(\dots)) = 2(2-2)(x - e) +$$

$$\cdot (x - e) + 2x^T Ax + (2-2)y^T Ay \leq 0$$

$$\nabla(x-y)^T \nabla(x-y) = x^T \nabla x - 2x^T \nabla y + y^T \nabla y$$

λ_0 $\rightarrow 0$
 λ_0 $\rightarrow 0$

! c bewege $0 \iff$ auf der Achse
 λc - bewegung

max $f(x)$

s.t. $x \in C$

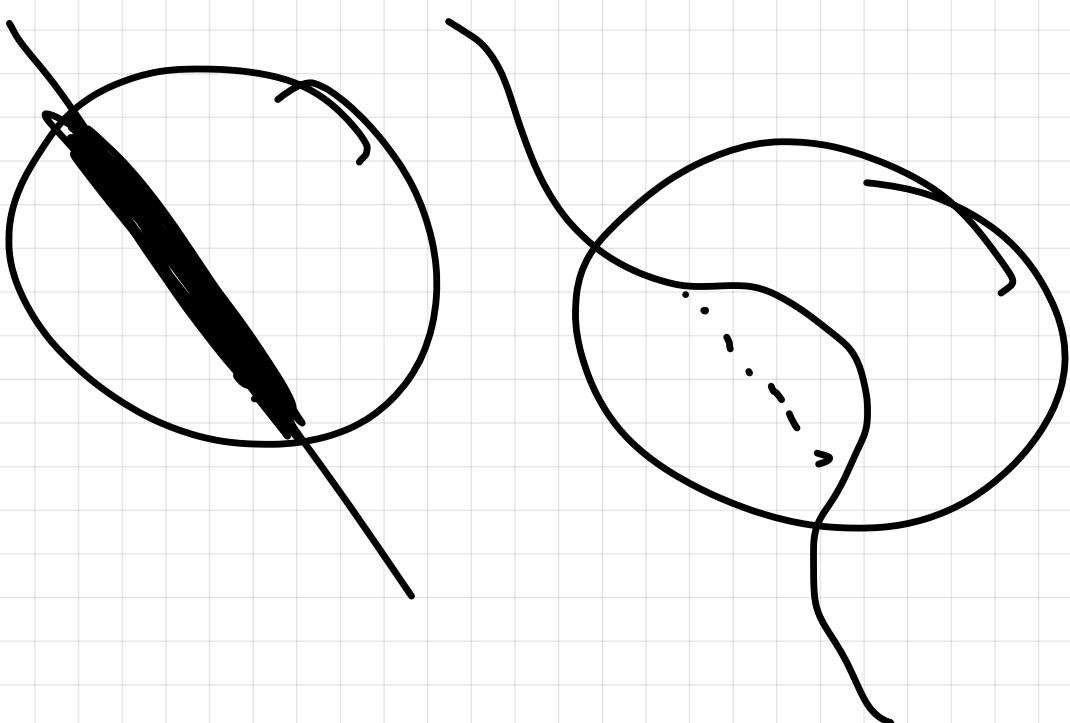
$\varrho(x) \leq c$ - $\varrho(x)$ - beschränkt
durch c

↑
str concave

$$\varrho(2x + (1-2)y) \leq 2\varrho(x) + (1-2)\varrho(y)$$

↑
str convex

$\varrho(x) = c$ - $\varrho(x)$ - oben K
oben



Convex

$\min f(x)$ - convex

s.t. $x \in C$

Concave

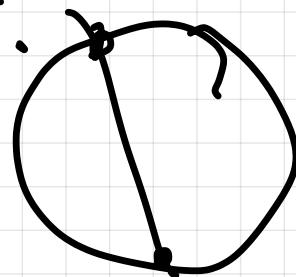
$\max f(x)$ - concave

s.t. $x \in C$

$\left\{ \begin{array}{l} \min x \\ \text{s.t. } x^T v = b \end{array} \right.$

$\left\{ \begin{array}{l} \max x \\ \text{s.t. } x^T v = b \end{array} \right.$

$$\boxed{V > 0}$$



$\left\{ \begin{array}{l} \max x \\ \text{s.t. } x^T v = b \end{array} \right.$

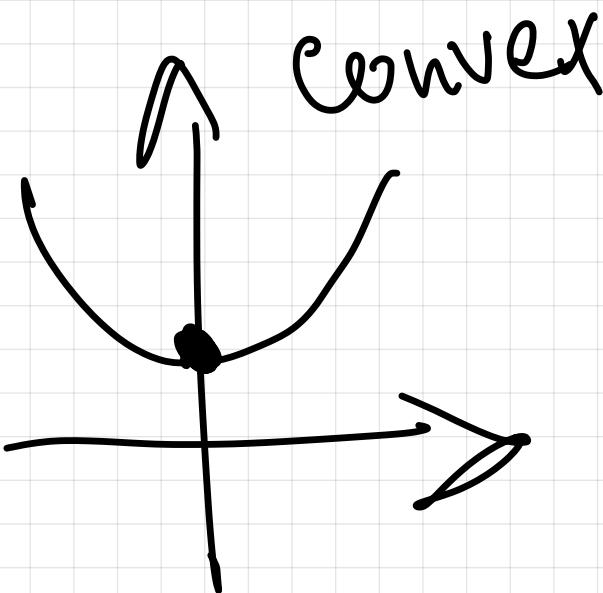
$\left\{ \begin{array}{l} \max x \\ \text{s.t. } x^T v = b \end{array} \right.$

No!

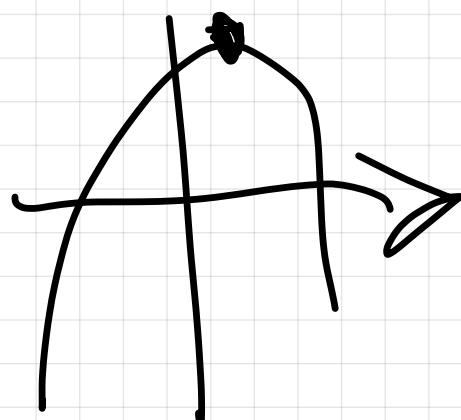
max $x^T c$

$$\text{S.t. } x^T Ax \leq l$$

Yes!

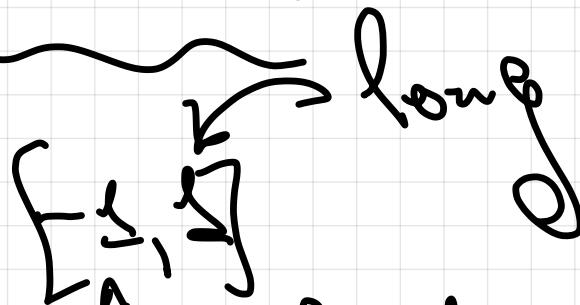


x concave



Markowitz model

x -shares



$$\sum x_i = 1$$

1,2

π - return

2010

$$r = 3\%$$

$$\frac{P_2 - P_1 + g}{P_{t-1}} = r$$

$$\sum_i x_i p_i = x^T p = \bar{x}$$

Assets \rightarrow Σ -covariance

$x^T \Sigma x$ - Variance of portfolio

$$\min x^T \Sigma x$$

$$\text{Var}(x \cdot \alpha) = x^T \Sigma x$$

$$\begin{aligned} \text{s.t. } & x^T \Sigma e = d \\ & x^T \alpha = \bar{\alpha} \end{aligned}$$

$$\max -x^T \Sigma x$$

$$\text{s.t. } \dots$$

$$L = \frac{1}{2} \|x\|^2 + \alpha(x^T e - g) + \lambda(x^T n - r_p)$$

Optimierung über

$$g(x) \geq c \quad \nabla(g(x) - c) = 0$$

$$\begin{aligned} \nabla L &= \nabla x + \alpha e + \lambda n = 0 \\ \nabla(x^T e - g) &= 0 \quad \nabla(g(x) - c) = 0 \\ \nabla(x^T n - r_p) &= 0 \end{aligned}$$

$$X = \underbrace{2\sqrt{-s}\sigma}_{\text{Wavy line}} + \underbrace{\sqrt{-s}\sigma}_{\text{Wavy line}}$$

$$\underbrace{2\sqrt{-s}\sigma}_{\text{Wavy line}} + \underbrace{\sqrt{-s}\sigma}_{\text{Wavy line}} = \rho$$

$$2\sqrt{-s}\sigma + \sqrt{-s}\sigma = 1$$

$\sqrt{-s}$ -veeee. mehr oder weniger

$$\rho = \begin{pmatrix} \sqrt{-s}\sigma & \sqrt{-s}\sigma \\ \sqrt{-s}\sigma & \sqrt{-s}\sigma \end{pmatrix}$$

$$\sqrt{-s} \begin{pmatrix} \rho & \sigma \\ \sigma & \rho \end{pmatrix} = \begin{pmatrix} \rho & \sigma \\ \sigma & \rho \end{pmatrix}$$

$$\text{Diagram showing } \text{Diagram} = \text{Diagram}$$

$$x = \left(\begin{matrix} \sqrt{-1} & 0 \\ 0 & 1 \end{matrix} \right) \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) =$$

$$= \sqrt{-1} r \cdot j + \sqrt{-1} e \cdot i$$

$$x = \left(\begin{matrix} \sqrt{-1} & 0 \\ 0 & 1 \end{matrix} \right) \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) \cdot \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right)$$

$$x^T \cdot x = \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) \cdot \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) =$$

$$\cdot \left(\begin{matrix} \sqrt{-1} & 0 \\ 0 & 1 \end{matrix} \right) \cdot \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) \cdot \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right) =$$

$$x_{\text{left}} = \begin{pmatrix} x_1 & x_2 \\ x_2 & x_1 \end{pmatrix}$$

$$(e^{\frac{x_1}{2}} e^{-\frac{x_2}{2}}) \begin{pmatrix} v^{-1} & 0 \\ 0 & v^{-1} \end{pmatrix} = V_p$$

$$\begin{pmatrix} v^{-1} & 0 \\ 0 & v^{-1} \end{pmatrix} \dots \begin{pmatrix} v^{-1} & 0 \\ 0 & v^{-1} \end{pmatrix} = V_p \quad Q = \text{up. ones}$$

$$x^T V_x = (v_{p1} v_{p2} \dots v_{pn}) \begin{pmatrix} v_{p1} & v_{p2} & \dots & v_{pn} \end{pmatrix},$$

$$= \begin{pmatrix} v_{p1} & v_{p2} & \dots & v_{pn} \end{pmatrix} \begin{pmatrix} v_{p1} & v_{p2} \\ v_{p2} & v_{p1} \end{pmatrix} = 6^2$$

$$\sqrt{-1} \rho = \begin{pmatrix} A & B \\ B & C \end{pmatrix}$$

$$A = \sqrt{-1} \rho$$

$$B = \sqrt{-1} \rho$$

$$C = \sqrt{-1} \rho$$

$$\sqrt{\rho} = \begin{pmatrix} e^{-B/2} & \\ & -B/A \end{pmatrix}$$

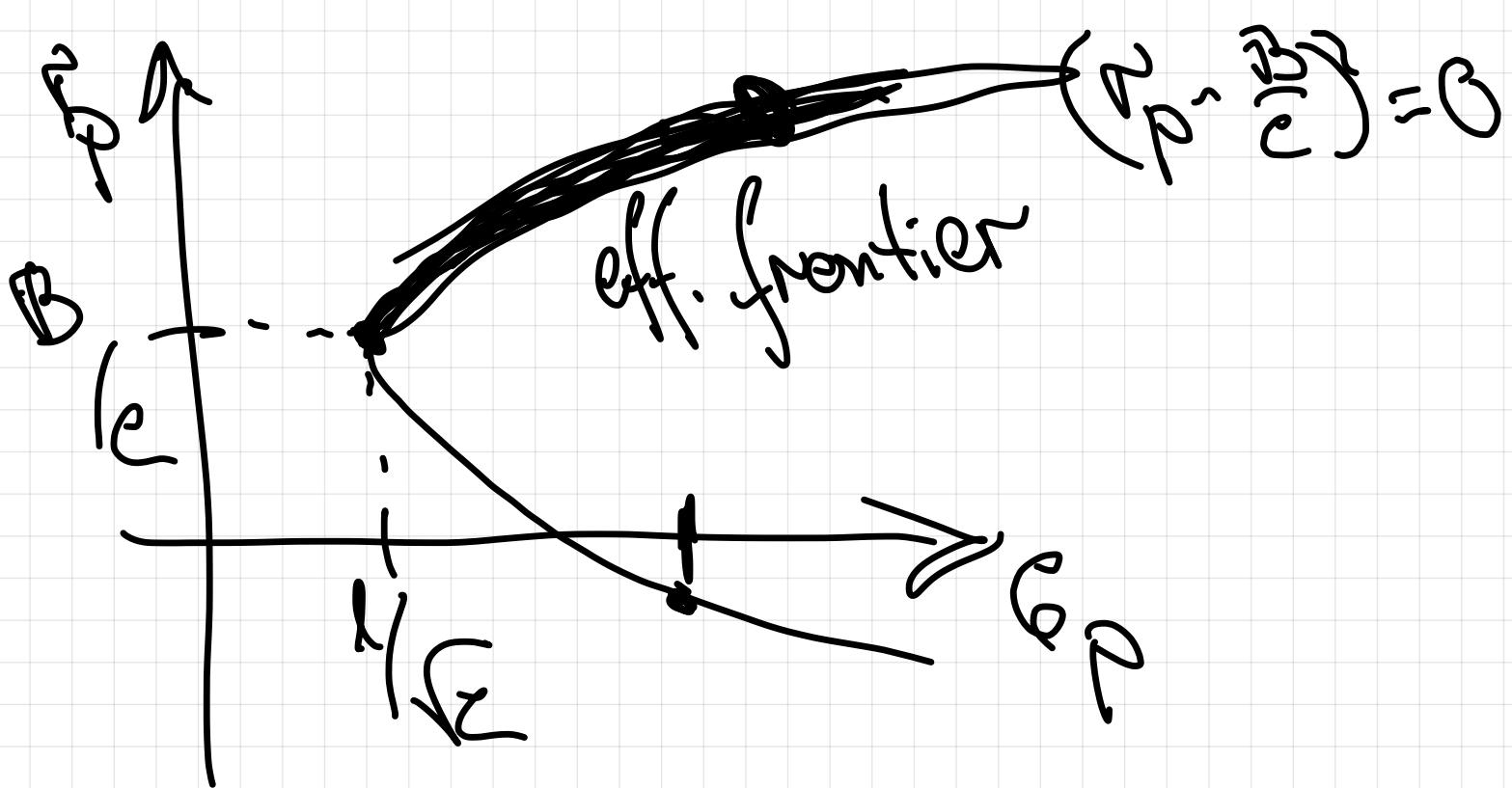
$$\underbrace{G_P^2}_{\text{def}} = (\sqrt{\rho})^{-1} \cdot \begin{pmatrix} e^{-B} & \\ -B & A \end{pmatrix} \begin{pmatrix} \sqrt{\rho} \\ 1 \end{pmatrix} =$$

$$= \frac{e}{D} \left(\sqrt{\rho}, \frac{B}{e} \right)^T + \frac{1}{e}$$

$e > 0, A > 0$

$D > 0$

$$G_P^2 - \frac{e^2}{D} \left(\sqrt{\rho}, \frac{B}{e} \right)^T = g$$



A hand-drawn diagram showing the derivation of the Capital Allocation Line (CAL) from the Efficient Frontier.

The vertical axis is labeled \bar{r} and the horizontal axis is labeled σ .

The graph shows the Efficient Frontier (a concave curve) and the Capital Allocation Line (a straight line passing through the origin).

The derivation is shown as follows:

$$\min_{x \geq 0} x^T \Sigma x$$

$$x^T \Gamma = r_p$$

$$x^T Q = g$$

$$x \geq 0$$

The last two equations are grouped by a brace on the left, indicating they are constraints for the optimization problem.

To the right, the resulting Capital Allocation Line is shown as:

$$\min_{x \geq 0} x^T \Sigma x$$

$$\sim x \geq 0$$

$$L = -\frac{1}{2} \int_{\Gamma} \int_{\Gamma} x^T \nabla u + \lambda (x^T r - r_p) +$$

$$+ \nu e(x^T e - \zeta) + \Omega^T x$$

$\zeta = R - T$

minimum,

$$\frac{\partial L}{\partial x} = \nabla x + \Omega r + \nu e + \zeta = 0$$

$$(x^T r - r_p) = 0$$

$$(x^T e - \zeta) = 0$$

$$\nu e - \zeta$$

$$\therefore x = 0$$

$$so \quad < 0$$

$$x \geq 0$$

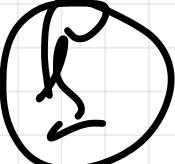
!

$$x=0 \rightarrow \nu + \mu - \zeta \leq 0$$

↑ ↑ ↑

so so so

Cerebral 2


$$u(x) = (d_1 x_1 + d_2 x_2)^{\frac{1}{\rho}}$$

$\rho \in (-\infty, 1)$ CES - constant
classification of
substitution
functions

Max $u(x)$

s.t. $P_1 x_1 + P_2 x_2 \leq w$

$\hookrightarrow u(x)$ - concave

CES - concave?

$$f''(x) < 0$$

$$\forall x$$

$$\exists f''(x) < 0$$

strictly concave!

$$g(x) - \text{concave}$$

$$g(x) > 0$$

$$s(x) = g(x)^2 - \text{concave?}$$

$$s'(x) = 2g^{2-1}(x)g'(x)$$

$$s''(x) = 2(2-1)g^{2-2}(x)(g'(x))^2 +$$

$$+ 2g^{2-2}(x)g''(x) > 0$$

$$2g^{2-2} > 0$$

$$2(2-1) > 0$$

$$2-1 > 0$$

$$2 > 1$$

$$2 \in (0, 5)$$

$$U(x) = \underbrace{(2x_1 + 2x_2)}_{P} P$$

$$P \in (-\infty, 1]$$

$$P \in [0, 1]$$

$$\frac{1}{P-1} = 1$$

$$P \in [0, 1]$$

$$P \in [0, 1]$$

$$\frac{2x_1}{P-1} = 2x_1 + P^{-1}$$

$$(\dots) \leq 0$$

$$\frac{2x_2}{P-1} = 2x_2 + P^{-1}$$

$$(\dots) \leq 0$$

$$P \in [0, 1]$$

$$P \in [0, 1]$$

$$P(P-1) \leq 2x_1 + P^{-1}$$

$$P(P-1)$$

$$P \in [0, 1]$$

$$P(P-1) \leq 0$$

$$P(P-1) \leq 0$$

$$P(P-1) \leq 2x_2 + P^{-1}$$

$$P(P-1)$$

$$P \in [0, 1]$$

$$L = (Q_1 x_1 p_1 + Q_2 x_2 p_2) \delta + Q(w - p_x)$$

$$w \geq p_x \quad (c_j - p_j)$$

$$x_1 \leq x_2 \geq c$$

$$\frac{\partial L}{\partial x_1} = Q_1 x_1 p_1 \quad (\dots)$$

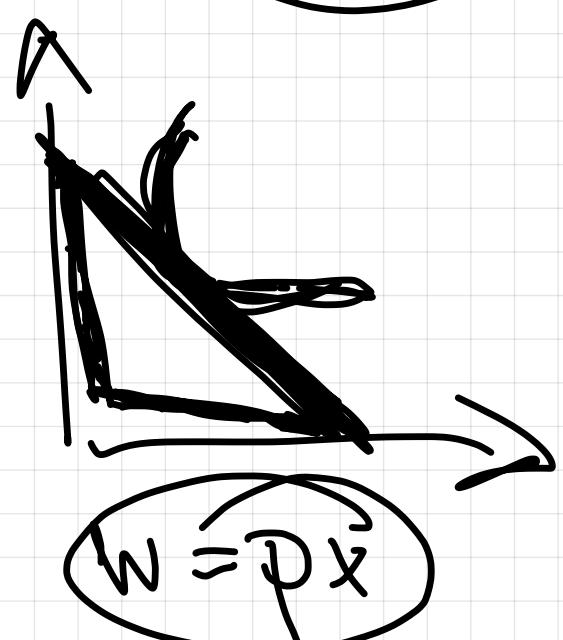
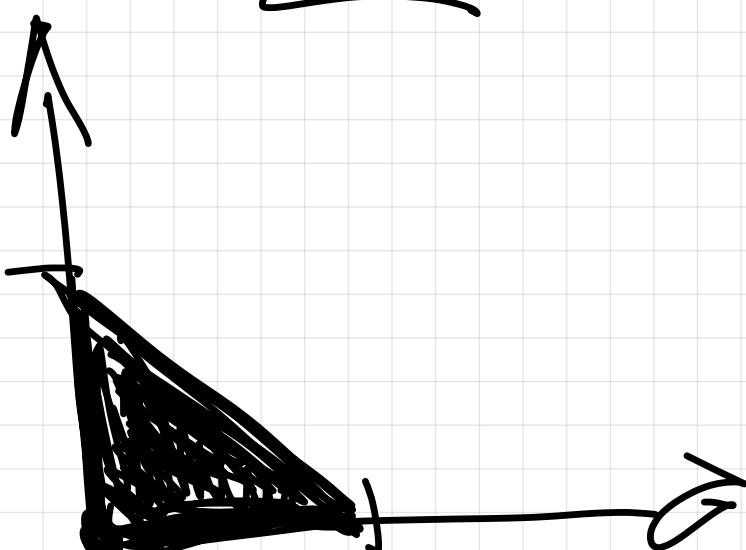
$$- Q_1 p_1 = 0$$

$$\frac{\partial L}{\partial x_2} = Q_2 x_2 p_2 \quad (\dots)$$

$$- Q_2 p_2 = 0$$

$$Q(w - p_x) = 0$$

KKT condition



$$\frac{P_1}{P_2} \cdot \left(\frac{x_1}{x_2} \right)^{P_1 - 1} = \frac{P_1}{P_2}$$

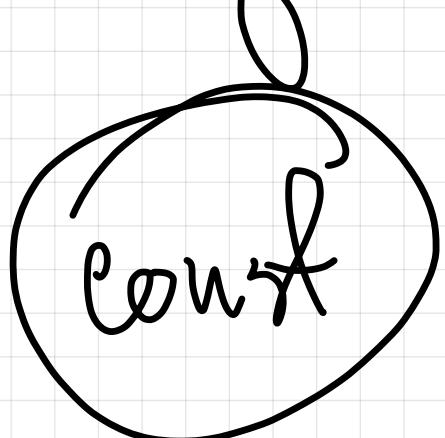
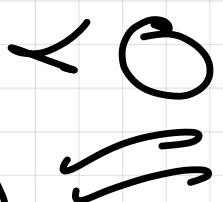
$$\ln \frac{P_1}{P_2} + (P_1 - 1) \ln \frac{x_1}{x_2} = \ln \frac{P_1}{P_2}$$

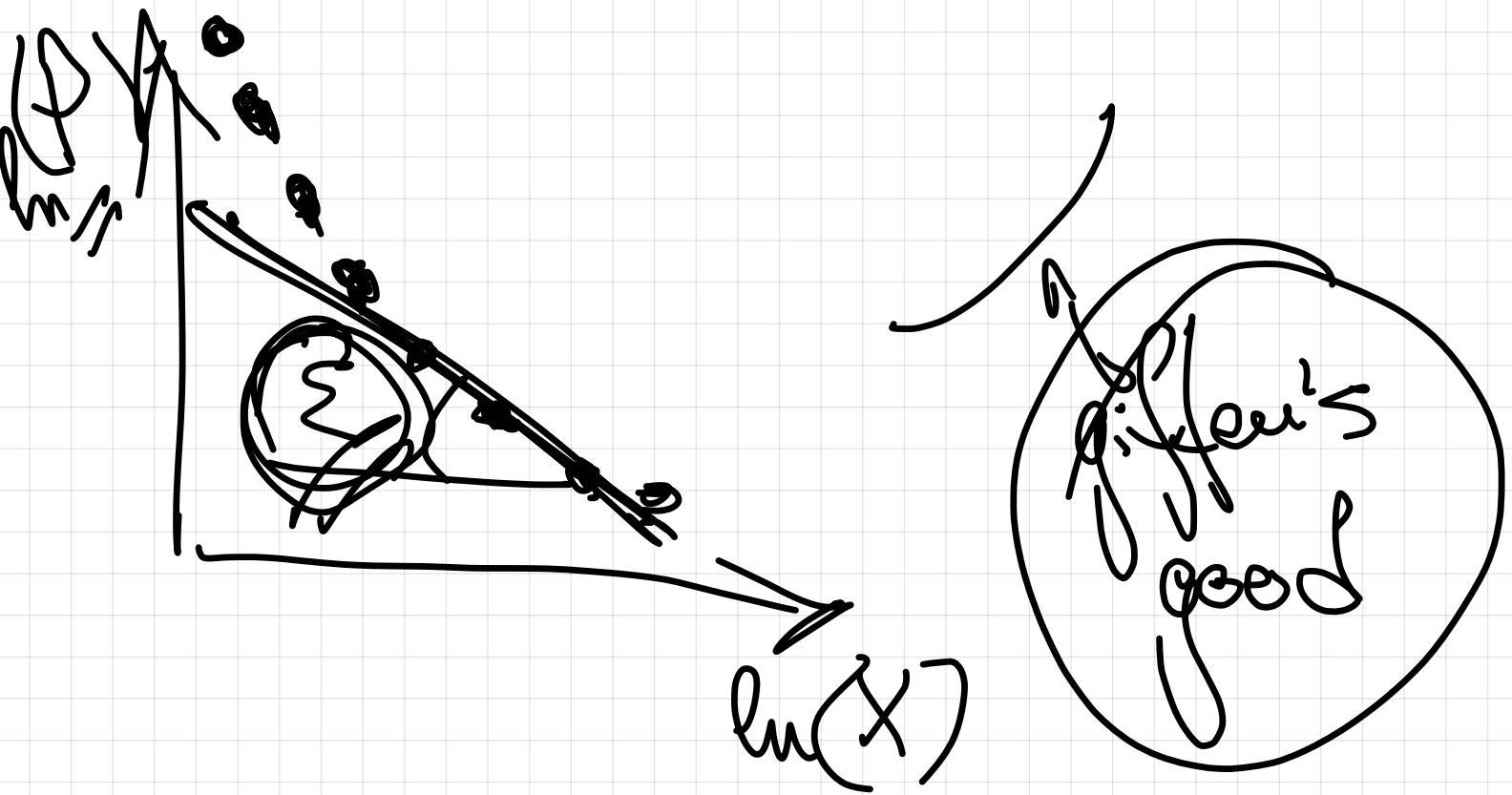
$$\ln \frac{x_1}{x_2} = \frac{1}{P_1 - 1} \ln \frac{P_1}{P_2} + C$$

$$\frac{dx}{x} = \frac{P}{P_1} dP$$

$\frac{dx}{x} = \frac{P}{P_1} dP$ = Σ - Dialektreeffekt
generalisiert

$$\Sigma = \frac{l}{l - s}$$





$$\frac{\partial}{\partial x_2} \left(\frac{x_1}{x_2} \right) = \frac{P_1}{P_2}$$
$$P_1 x_1 + P_2 x_2 = w$$
$$x_1 = x_2 \cdot \left(\frac{P_2}{P_1} - \frac{w}{x_2} \right)$$

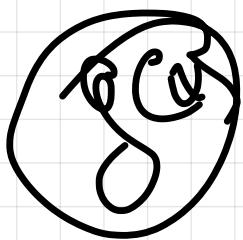
$$P_1 \cdot \left(\frac{P_2}{P_1} \cdot \frac{\alpha_1}{\alpha_2} \right)^{\frac{1}{1-P}} x_1 + P_2 x_2 = \omega$$

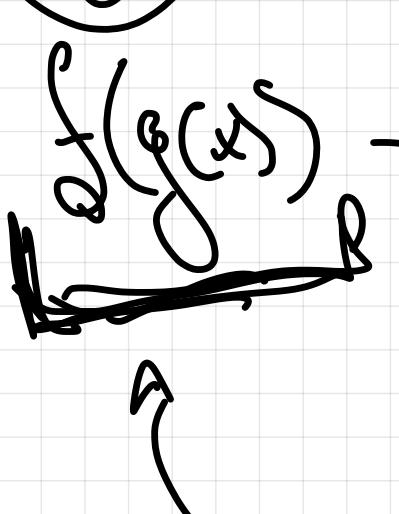
$$P_2 x_2 \left(\frac{P_1}{P_2} \cdot \frac{\alpha_1}{\alpha_2} \right)^{\frac{1}{1-P}} + \frac{1}{1-P} = \omega$$

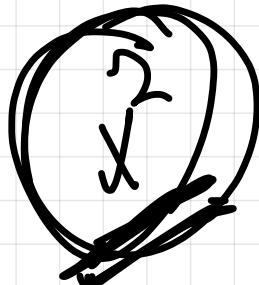
$$\frac{1}{1-P} = \frac{P}{1-P}$$

$$x_2 = \omega \cdot \left(1 + \frac{\alpha_1}{\alpha_2} \right)^{\frac{1}{1-P}} \cdot \left(\frac{P_1}{P_2} \right)$$

$$x_2 = \left(1 + \frac{\alpha_1}{\alpha_2} \right)^{\frac{1}{1-P}} \cdot \left(\frac{P_1}{P_2} \right)$$

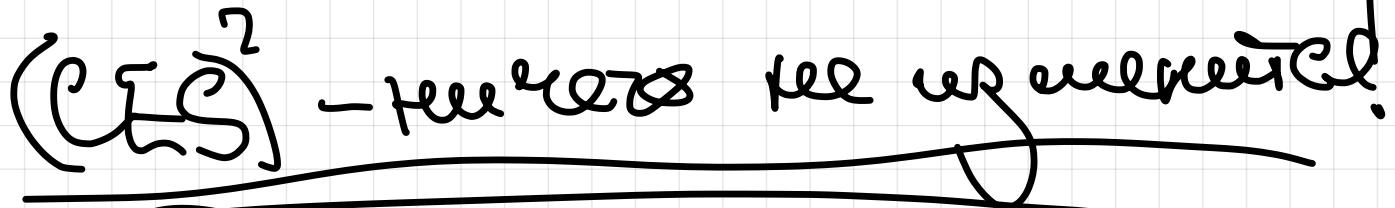
 - concave max

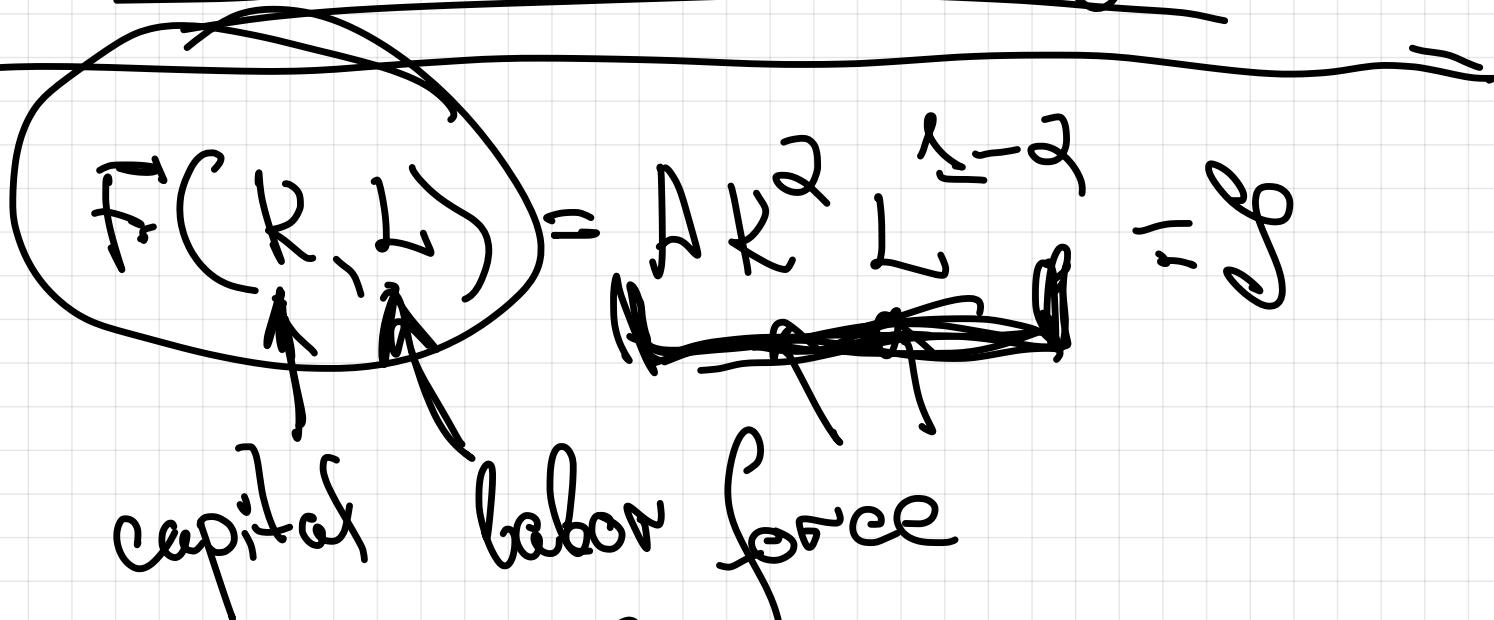
 - convex?



convex + monotone

convex (concave) - concave

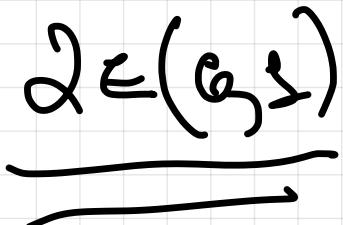
 - returns to scale increasing!



$$F(K, L) = AK^{\alpha} L^{1-\alpha} = g$$

capital labor force

1) F - concave



2) Geometric intuition

$K, L \rightarrow \gamma K, \gamma L$

$y \rightarrow \gamma y$

$$wK + wL = \text{coste}$$

generación

$$\text{min} \{ wK + wL \}$$

$$\text{s.t. } F(K, L) \geq Q$$

$$Q = -wK - wL + \gamma (AK^{\alpha}L^{1-\alpha} - Q)$$

$$\frac{\partial Q}{\partial K} = -w + \gamma \alpha A \left(\frac{L}{K}\right)^{1-\alpha} = 0$$

$$\frac{\partial Q}{\partial L} = -w + \gamma (1-\alpha) A \left(\frac{K}{L}\right)^{\alpha} = 0$$

$$\gamma (AK^{\alpha}L^{1-\alpha} - Q) = 0$$

$$\gamma \approx 0$$

$$K, L > 0$$

$$\alpha \frac{K}{L} \cdot \frac{L}{L} = \frac{\omega}{\frac{L}{L}}$$

Cobb-Douglas

CES function

$$\frac{p_1}{p_2} = \frac{\omega_1}{\omega_2}$$

$$\sum \approx -3$$

$$p_1 = p_2$$

$$\ln \frac{K}{L} = \frac{\omega}{2} - \ln \frac{L}{L}$$

$$K = L \cdot \frac{\omega}{\alpha} \cdot \frac{Q}{\frac{L}{L}}$$

$$\frac{K}{L} = \frac{Q}{L} \cdot \frac{L}{L} = Q$$

$$L^* = \frac{Q}{\alpha} \left(\frac{\omega}{\alpha} \right)^{\frac{1}{1-\alpha}} \cdot \left(\frac{\omega}{\alpha} \right)^{\frac{1}{1-\alpha}}$$

$$K^* = \frac{Q}{\alpha} \left(\frac{\omega}{\alpha} \right)^{\frac{1}{1-\alpha}} \cdot \left(\frac{\omega}{\alpha} \right)^{\frac{1}{1-\alpha}}$$

$$z \cdot f^*(q, w, z) + w \cdot h^*(q, w, z) =$$

$\frac{1}{A} \cdot \pi r^2 \cdot \left(\frac{w}{2}\right)^{1-\alpha} = C(w, r, q)$

Global Envelope theorem!

$$f(x; \alpha) \rightarrow f(x(\alpha); \alpha)$$

$$\frac{\partial f}{\partial \alpha} = \frac{\partial f}{\partial \alpha} + \frac{\partial f}{\partial x} \cdot \frac{\partial x}{\partial \alpha} >$$

$$x^*(\alpha) =$$

$$\frac{\partial f}{\partial \alpha} = \frac{\partial f}{\partial \alpha}$$

with restrictions

$\mathcal{L}(\alpha)$

$$\frac{\partial \mathcal{L}(\alpha)}{\partial \alpha} = \sum \mathcal{L}^*(\alpha^*(\alpha); \alpha) +$$

$$+ \sum \mathcal{L}^*(\alpha) \frac{\partial \mathcal{L}}{\partial \alpha} (\alpha^*(\alpha), \alpha)$$

$$C(q, n, w) = \frac{1}{n!} \left(\frac{q}{\alpha} \right)^{\alpha} \left(\frac{w}{n-\alpha} \right)^{n-\alpha}$$

Using Envelope theorem

$$\frac{\partial C}{\partial \alpha} = \alpha^*$$

$$\frac{\partial C}{\partial w} = L^*$$

$$\frac{\partial C}{\partial q} = -J^*$$

$$L = \omega K + \omega L + \alpha (F(K, L) - \alpha)$$

$$\frac{\partial L}{\partial \dot{w}} = \frac{\partial L}{\partial w} = \alpha F^*(w, r, q)$$

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \dot{w}} = 1^* (w, r, q)$$

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial \dot{x}} = x^* (x, \dot{x}, q) + \frac{\partial L}{\partial x}$$

$$\frac{\partial L}{\partial r} = A \cdot \left(\frac{w}{2^{-2}} \right)^{1-2} = A \cdot \left[\frac{w}{2^{-2}} \right]^{2-2} =$$

$$= \frac{A}{2} \cdot \left(\frac{w}{2^{-2}} \right)^{1-2} \cdot \left(\frac{2}{2^{-2}} \right)^{2-2}$$

$$\frac{\partial \mathcal{L}}{\partial w} = \frac{\partial f}{\partial w} \cdot \left(\frac{\partial f}{\partial w} \right)^T \cdot \left(\frac{z - p}{\sigma} \right)^T$$

$$\mathcal{L} = u(x) + \gamma(w - px)$$

$$\frac{\partial \mathcal{L}}{\partial p} = -\frac{\partial f}{\partial x}$$

Przygotujmy $u(x)$ takim, aby

$$\frac{\partial u^*}{\partial x} = -\frac{\partial f^*}{\partial x} x^* - f^*$$

Intuicja wg gospodarki
środowiskowej