Quantity vs Quality: Freshness and fishing trip length

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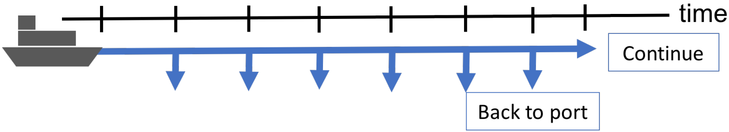
Fishing trip as optimal stopping

- Length of a fishing trip is a form of fishing effort (short run)
  - Choose the length directly (trip level data)?
    - LHS: length of a trip
  - Make decision if they continue the trip day by day?
    - Daily discrete choice



When they stop fishing?

- Binding constraint (e.g. storage)
- Optimal effort level?
- Revenue is concave
- But, daily catch on the beginning is not necessarily higher than daily catch end of a trip.

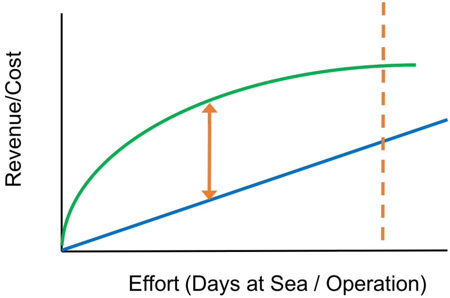


Figure: Concave revenue and cost

Why diminishing return?

- Daily catch decreases in days?
  - Harvest function $h = qE$ in short run
- Price decreases in days?
- Literature explains this by using utility.
  - Labour-Leisure substitution (Gautam et al, 1996, Stafford 2015)
    - Leisure enters the utility
    - Longer trip decreases leisure, and cause disutility.
  - Target-income/Reference-dependent (Nguyen and Leung 2013, Ran et al, 2014)
    - Marginal utility drops once the target level is met.

Hypothesis

- For this data, neither of these stories above hold.
  - Not much variation in leisure (days off)
  - Didn't find strong evidence of reference-dependent
- What causes diminishing return in utility or revenue?
  - In fishery context.

Hypothesis

- Deterioration of already-caught fish (i.e. freshness) cause a decreased return if a harvester continue the fishing trip.
    - If a harvester keep going fishing, the gain from quantity of fish increases.
    - The longer the trip is, the more the fish gets old and lose values
- Freshness affects price in the market (Ishimura & Baily 2013)
- Question: How harvesters perceive freshness?

Data description

- Offshore longline fishery in Kesennuma, Japan
  - Primarily targets Swordfish and Blue shark
  - Trip length is 40 days on average.
  - storages with ice (No freezers)
  - Operate in Pacific Ocean
- Daily log book data
  - Daily catch by species
    - Use only Oct-March for SF season

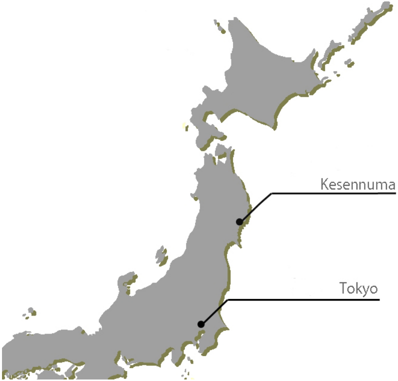


Figure: Location of Kesennuma

Key elements of the model

- Freshness
    - How much and when (how long ago) is the fish caught?
    - Daily level data allows us to compute the freshness of fish of given day
- Dynamic Decision
    - Expectation about rest of the trip given state variables
    - Trade-off between future gain from additional catch by continuing the trip, and deterioration of current harvest.

Daily decision with freshness

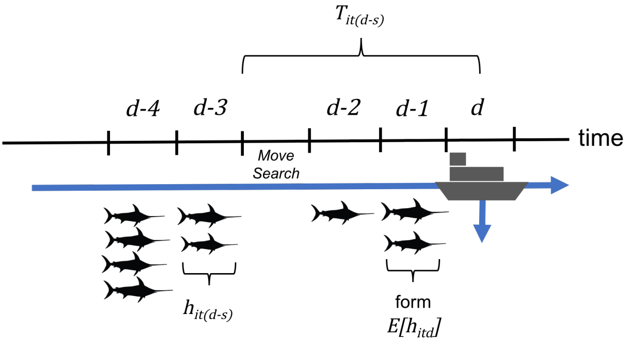
- First, look at the freshness only as a benchmark
- Latent Variable Model (Binary Discrete Choice)

$$U_{itd} = p_t \cdot E\left[h_{itd}\right] - d_{itd} - \sum_{s=1}^{d-2} \theta_{1(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)} + \varepsilon_{itd}$$

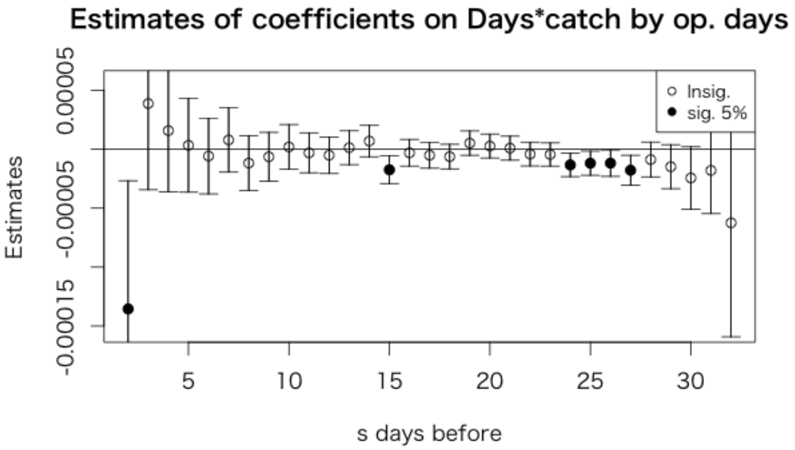
- Variables
  - p_t: price of fish
  - h_{itd}: amount of catch for vessel i in trip t on day d.
  - $T_{it(d-s)}$: Days past of fish caught $d - s$ operation days ago.
- Decision : Continue or Stop (return to the port)
- Estimation: Binary Logit

Daily decision with freshness

- Freshness term: $\sum_{s=1}^{d-2} \theta_{1(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)}$
- Example: $s = 3$ (3 operation days back),
  - $T_{it(d-3)} \cdot h_{it(d-3)}$ is "total freshness" of 3 op. days back
  - Large T implies less fresh, large h means more fish is affected by T.



Estimated Parameters



Dynamic Discrete Choice

- Distinguish contemporaneous variables and expectation of future gain
- Use value function for logit.

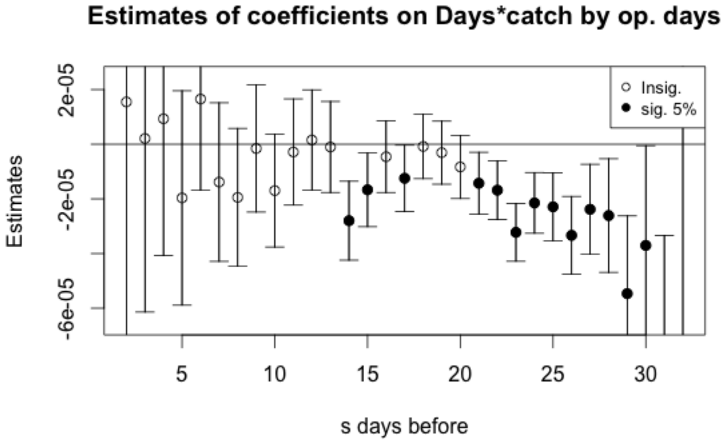
$$V_{itd} = p_t \cdot E\left[h_{itd}\right] - d_{itd} - \sum_{s=1}^{d-2} \theta_{1(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)} + \varepsilon_{itd} \\ \boxed{+E_d V\left(H', T', \varepsilon'\right)}$$

- How can we obtain the expectation term?

Dynamic Discrete Choice

- Estimation: Dynamic Logit (Rust, 1987)
- Estimation method: Two stage estimation
  - Hotz and Miller 1993, Bajari et al 2007, Huang & Smith 2014
  - 1st stage: Estimate the probability only with state variables
    - Use estimated probability to compute the expected term (Arcidiacono and Miller 2011)
    - Estimate the transtion probability of state variables
  - 2nd stage: Estimate the dynamic logit with the expectation term

Estimation Result



Estimation Result Highlight

- As expected, these coefficients are negative
  - After a certain days passed, harvesters start caring about freshness
- This freshness decay may be the reason why harvesters come back from the trip before the constraints bind.
  - Revenue exhibits diminishing marginal return, although quantity does not.
- The dynamic logit improve the estimation
  - Distinguish the contemporaneous effect and dynamic effect
  - The benchmark model is essentially a reduced form
    - High variances of coefficients

Diminishing return due to freshness measure

- $\frac{\partial Rev^2}{\partial^2 Day} < 0$, because of the freshness deterioration

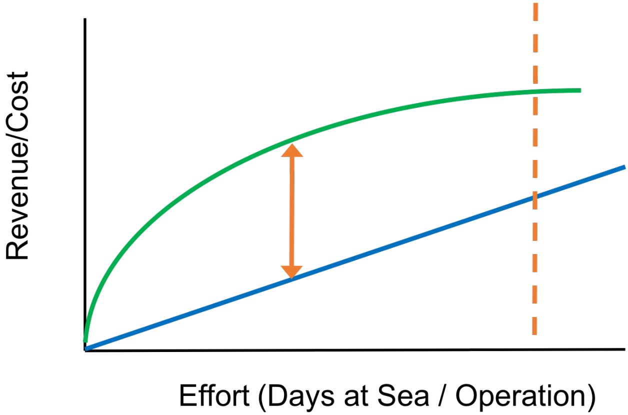


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Figure: Concave revenue and cost

Issues/Extentions

- Fitting a parametric function: decay rate specification

$$U_{itd} = p_t \cdot E\left[h_{itd} | H_{itd-1}\right] - \theta_1 - \sum_{s=1}^{d-1} \theta_2^{T_d - s} \cdot h_{its} + \varepsilon_{itd}^{Fish}$$

- Search behavior
  - Daily choice would be multinomial, {Fish, Search, Stop}
- Incorporate location choice (Hicks & Schnier 2006, 2008)
  - Jointly determine where and when to fish
  - location (distance) is an important state variable

Conclusion

- Harvesters face a trade-off between further harvest by additional day of a trip and loss of value by freshness deterioration.
- This trade-off affects the decision-making of trip length.
- Dynamic discrete choice model helps estimating the optimal stopping problem and clarify the contemporaneous effect of variables.

Project Summary

- Research Question
  - How do harvesters determine the length of a fishing trip?
- Hypothesis
  - Trade-off between additional catch and deterioration of freshness affects the length of a trip
- Approach
  - Dynamic discrete choice model
- Data
  - Longline offshore fishery (Swordfish & Blue shark) in Japan
- Result
  - A trip is likely to end as the caught fish gets older

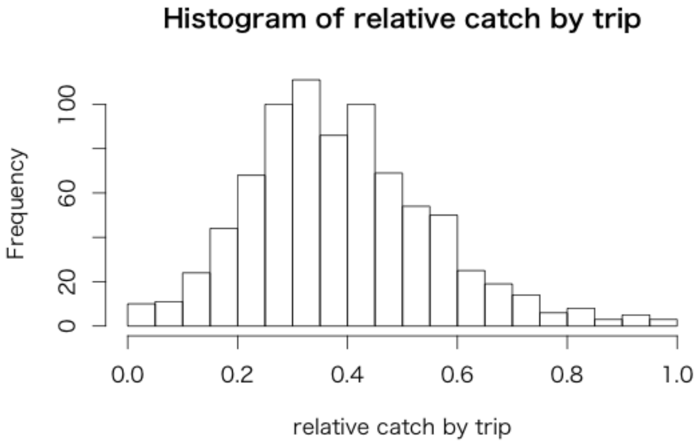
Application of the economic model

- Optmial stopping problem in natural resource use
    - Apply to other fishery, in particular offshore/high-sea
- Labour problem
    - "Area" choice for taxi drivers.
    - Self-employment vendors (e.g. Stadium Vendor, Oettinger 1999 JPE)

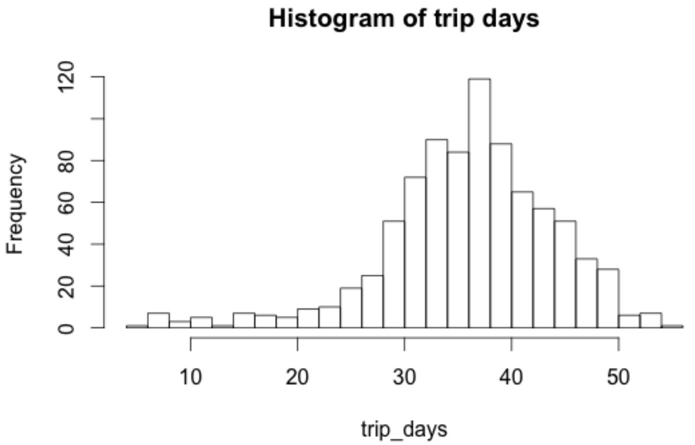
Are the constraints slack?

- If a constraint is binding, the linear production funtion story holds.
- Capacity constraint
  - Are vessels always full when get to port?
  - Check the total catch relative to the maximum amount in the data
- Fuel constraint
  - Do vessels always use up the fuel?
  - Check the days of trip.
    - If so, days of trip should be similar across trips.

Constraints?



Constraints?



Freshness Measure in Ishimura-Baily

- Freshness measure is time-weighted average of catch.

$$\lambda_{it}^{w} = \frac{1}{H_{ij}} \left[\sum_{d \in t} h_d^{ij} \cdot (t_{ij} - d_{ij}) \right]$$

- H_{ij}: total harvest of vessel i on a trip j
- h_d^{ij}: the harvest of a vessel at the dth day of the trip
- t_{ij}: total trip days of trip j
- d_{ij}: day in a trip j

Freshness Matters?

Table 1: Landing level ex-vessel price and freshness measure

	Dependent variable:			
	log(Sword Fish Unit Price)			
	(1)	(2)	(3)	(4)
$\log(\lambda)$	-0.090000^{***}	-0.185931^{***}	-0.165643^{***}	-0.116529^{***}
	(0.024883)	(0.022657)	(0.020771)	(0.019835)
SF Total Landing			-0.000009^{***}	-0.000013^{***}
			(0.000001)	(0.000001)
SF Unit Weight				0.004142^{***}
				(0.000368)
Constant	7.009251^{***}	7.241375^{***}	7.269219^{***}	6.881034^{***}
	(0.073865)	(0.082883)	(0.075796)	(0.078578)
Vessel FE	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Observations	874	874	874	874
R^2	0.014781	0.434745	0.528245	0.591121
Adjusted R^2	0.013651	0.402581	0.500798	0.566806

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Empirical model

- Translate the sequential problem explained above to Bellman equations (Rust, 1987)

$$V\left(H_{itd}, T_{itd}, \varepsilon_{itd}\right) = \max_{\{\delta_{itd}\}_{d}^{D_{it}}} E_d\left[\sum_{s=d}^{D_{it}} MU\left(H_{its}, D_{its}, \varepsilon_{its}, \delta; \theta\right) | H_{itd}, T_{itd}\right] \quad (1)$$

$$= \max_{\{\delta_{itd}\}_{d}^{D_{it}}} \left[MU\left(H_{itd}, T_{itd}, \delta; \theta\right) + \varepsilon_{itd} + E_d V\left(H_{itd+1}, T_{itd+1}, \varepsilon_{itd+1}\right)\right]$$

  - T_{itd}, the days passed, and H_{itd} are treated as state variables.
  - ε_t is unobserved factors that affect utility

Choice specific value function

- The binary discrete choice problem can be written as

$$V\left(H_{itd}, T_{itd}, \varepsilon_{itd}\right) =$$
$$\max\left\{\tilde{V}\left(H_{itd}, T_{itd}, \varepsilon_{itd}, \delta_{itd} = Fish\right), \tilde{V}\left(H_{itd}, T_{itd}, \varepsilon_{itd}, \delta_{itd} = Return\right)\right\}$$

- $\tilde{V}$ indicates "choice-specific" value function

$$\tilde{V}\left(H, T, \varepsilon, \delta = Fish\right) = MU^{Fish}\left(H, T, \varepsilon, \delta = Fish; \theta\right) + E_d V\left(H', T', \varepsilon'\right) \tag{2}$$
$$\tilde{V}\left(H, T, \varepsilon, \delta = Return\right) = MU^{Return}\left(H, T, \varepsilon, \delta = Return; \theta\right) \tag{3}$$

  - Since "Return" is a terminal decision, no expectation term.

Derivation of expectation

$$
\begin{aligned}
& E_d V\left(H', T', \varepsilon'\right) = \\
& \ln\left\{\exp\left(\bar{MU}^{return}\right) \frac{\exp\left(\bar{MU}^{Fish} + E_d V\left(H', T', \varepsilon'\right)\right) + \exp\left(\bar{MU}^{return}\right)}{\exp\left(\bar{MU}^{return}\right)}\right\} + \gamma \\
= \quad & \ln\left\{\exp\left(\bar{MU}^{return}\right)\left[\exp\left(\bar{MU}^{Fish} + E_d V\left(H', T', \varepsilon'\right) - \bar{MU}^{Return}\right) + 1\right]\right\} + \gamma \\
= \quad & \bar{MU}^{return} + \ln\left\{\left[\exp\left(\bar{MU}^{Fish} + E_d V\left(H', T', \varepsilon'\right) - \bar{MU}^{Return}\right) + 1\right]\right\} + \gamma \\
= \quad & \bar{MU}^{return} - \ln\left\{\frac{1}{\left[1 + \exp\left(\bar{MU}^{Fish} + E_d V\left(H', T', \varepsilon'\right) - \bar{MU}^{Return}\right)\right]}\right\} + \gamma
\end{aligned}
$$

Specification

- Marginal Utility

$$MU_{itd}^{Fish} = p_t \cdot E\left[h_{itd}\right] - \theta_1 - \sum_{s=1}^{d-2} \theta_{2(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)} + \varepsilon_{itd}^{Fish}$$

$$\begin{aligned} MU_{itd}^{Return} &= \bar{MU}_{itd}^{Return} + \varepsilon_{itd}^{Return} \\ &= -\theta_3 + \varepsilon_{itd}^{Return} \end{aligned} \quad (4)$$

- θ_1: cost of operation
- $\theta_{2(d-s)}$: coefficients on the interaction of catch and passed calendar days of catch
  - These coefficients represent the freshness.
  - The interaction term is large when past catch is large or the $d-s$th day catch is old.
- θ_3: cost of return. An issue here is that θ_1 and θ_3 are not identified.

Estimation: Dynamic Logit

- Static Logit: $RandomUtility_t = U_t^{Fish} + \varepsilon^{Fish}$

$$Pr\left(\delta = Fish\right) = \frac{\exp\left(U^{Fish}\right)}{\exp\left(U^{Fish}\right) + \exp\left(U^{return}\right)}$$

- Dynamic Logit:
$RandomUtility = U^{Fish} + \varepsilon^{Fish} + E\left[RandomUtility_{t+1}\right]$

$$Pr\left(\delta = Fish\right) = \frac{\exp\left(U^{Fish} + E\left[RU\right]\right)}{\exp\left(U^{Fish} + E\left[RU\right]\right) + \exp\left(U^{Return} + E\left[R\right.\right.}$$

Estimation method: two-step approach

- Two step approach (Hotz & Miller 1993, Bajari, et. al. 2007, & Arcidiacono and Miller 2011)
  1. Estimate the probability of choice based on state variables by reduced form, and transition probability of state variables
  2. Compute the expected value function term and estimate the structural parameters by dynamic logit.

1st Step: Probability of choice

- Reduced form estimation of choice probability

$$\hat{Pr}\left(\delta = Return | T, H\right) =$$

$$\frac{\exp\left(\lambda_0 + \lambda_1 h_{it(d-1)} + \sum_{s=1}^{d-2} \lambda_{2(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)}\right)}{1 + \exp\left(\lambda_0 + \lambda_1 h_{it(d-1)} + \sum_{s=1}^{d-2} \lambda_{2(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)}\right)}$$

$$\hat{Pr}\left(\delta = Fish | T, H\right) = 1 - \hat{Pr}\left(\delta = Return | T, H\right)$$

  - Use flexible logit
  - Nonparametric estimation would be ideal.

1st Step: Transition probability

- Transition of “passed days”

$$\hat{G}_T\left(T'|T,\delta\right) = \sum_{t=1}^{R}\sum_{d=1}^{D_{it}-1}\frac{1}{\sum_i\sum_t\sum_d\left(T_{itd}=T,\delta=Fish\right)}I\left(T_{itd+1}\leq T',T_{itd}=T,\delta=Fish\right)$$

- Intuitively, passed days are deterministic.
- Operation days v.s. calender days
  - The data unit is operation day. Freshness maybe affected by calender days.
  - Next operation day may be tomorrow, 2 days later, or 3 days later.
  - “Search” behavior is obscured in this simple model.

1st Step: Transitional probability

- Transition of past catch

$$h_{itd} = \gamma h_{itd-1} + \varepsilon_{itd} \tag{5}$$

  - conditional expected catch $E\left[h_{itd} | h_{itd-1}\right]$ is estimated by lag one autoregressive (AR) model.

2nd Step: Form expectation

- Following Arcidiacono and Miller (2011)
- Assume additivity of unobserved factor, and its distribution is i.i.d. Type 1 extreme value, the expectation is expressed as the log-sum term.

$$
\begin{aligned}
& E_d V\left(H', D', \varepsilon'\right) = \\
& \int \max_{\delta} \left\{ \tilde{V}^{Fish}\left(\varepsilon^{Fish}\right), \tilde{V}^{Return}\left(\varepsilon^{Return}\right) \right\} f(\varepsilon)\, d\varepsilon \\
= \quad & \ln \left\{ \exp\left(\bar{M}U^{Fish} + E_d V\left(H', D', \varepsilon'\right) \right) + \exp\left(\bar{M}U^{return} \right) \right\} + \gamma
\end{aligned}
$$

2nd Step: Form expectation

- This can be rewritten as

$$
\begin{aligned}
& E_d V\left(H', D', \varepsilon'\right) = \\
& \bar{MU}^{return} - \ln \left\{ \frac{1}{\left[1 + \exp\left(\bar{MU}^{Fish} + E_d V\left(H', T', \varepsilon'\right) - \bar{MU}^{Retu}\right.\right.} \right. \\
= \quad & -\ln\left\{Pr\left(\delta = Return | T', H'; \theta\right)\right\} + \gamma
\end{aligned}
$$

  - the second equality holds because the inside of the blacket is choice probability for $Return$
    - we set the marginal utility for $Return$ as zero (normalization).

2nd Step: Form expectation

- Use estimated $\hat{P}r\left(\delta = Return|T, H\right)$ to obtain these values
- This term is conditional on state variables.
- Integrate over probabilities of state variables.

$$E_d V\left(H_t, D_t, \varepsilon'\right) =$$
$$-\int\int \ln\left\{\hat{P}r\left(\delta = Return|T_d, H_d;\theta\right)\right\}\hat{G}_T\left(T'|T\right)\hat{G}_H\left(H'|H\right) + \gamma$$

2nd Step: Estimate structural parameters

- Estimate parameters with the dynamic logit using the expectation term.

$$Pr\left(\delta_{itd} = Fish | T_{itd}, H_{itd}\right) = \frac{\exp\left(\bar{MU}_{itd}^{Fish} + \varepsilon + E_d V\left(H_{itd}, D_{itd}, \varepsilon\right)\right)}{1 + \exp\left(\bar{MU}_{itd}^{Fish} + \varepsilon + E_d V\left(H_{itd}, D_{itd}, \varepsilon\right.\right.}$$

where

$$\bar{MU}^{Fish} = p_t \cdot E\left[h_{itd}\right] - \left(\theta_1 + \theta_3\right) - \sum_{s=1}^{d-2} \theta_{2(d-s)} \cdot T_{it(d-s)} \cdot h_{it(d-s)}$$