

# ASSESSING LONG-TERM BENEFITS OF IMMUNOTHERAPY BASED ON EARLY TUMOR ASSESSMENT DATA

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## Disclosures

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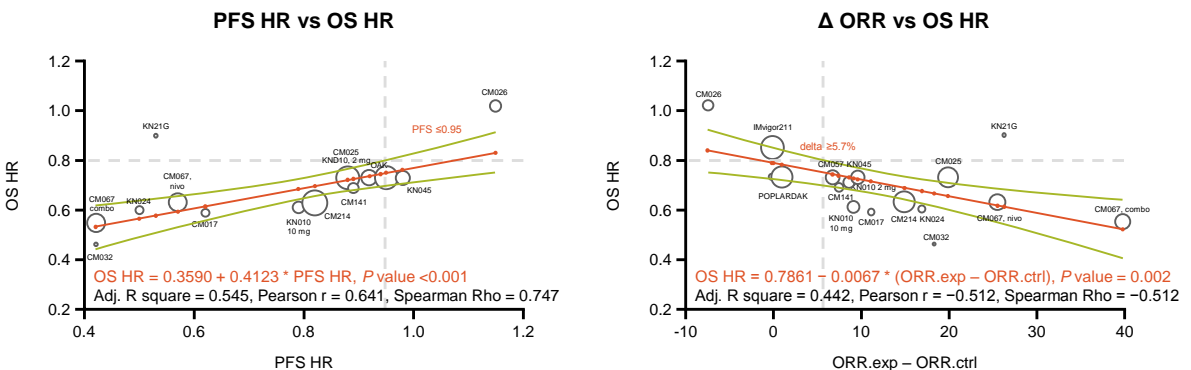
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# Background

- The emerging data in immuno-oncology have changed the way many cancers are being treated
- Clinically meaningful benefits in OS have been observed in many tumor types, including NSCLC, melanoma, renal cell carcinoma and SCCHN
- OS remains the gold standard of clinical benefit in patients with cancer
- However, challenges remain with detecting OS benefits, including duration of follow-up, crossover and competing risks (in earlier disease settings)
- PFS and ORR are often not reliable surrogates for predicting OS
- What novel approaches can be considered for making an early assessment?

NSCLC, non-small cell lung cancer; ORR, objective response rate; OS, overall survival; PFS, progression-free survival; SCCHN, squamous cell cancer of the head and neck

## Modest correlation of PFS HR vs OS HR and Δ ORR vs OS HR in patients treated with I-O vs chemotherapy in various solid tumors



Modest improvements in PFS may result in a large improvement in OS

Modest improvements in ORR may result in a large improvement in OS

**A PFS HR ≤ 0.9 or Δ ORR > 10% may be associated with an OS HR of ≤ 0.8**

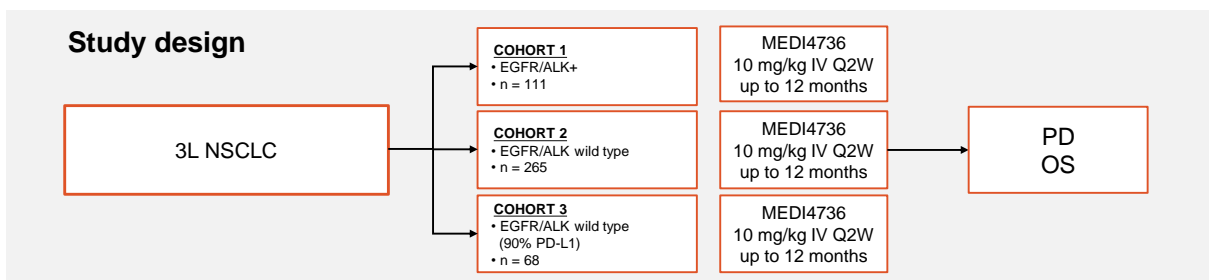
Adj, adjusted; CM, CheckMate; ctrl, control; exp, experimental; HR, hazard ratio; I-O, immuno-oncology; KN, Keynote; ORR, objective response rate; nivo, nivolumab; OS, overall survival; PFS, progression-free survival; SCCHN, squamous cell cancer of the head and neck

# Tumor kinetics modeling: an alternative approach?

- Using **baseline characteristics** and **early tumor assessment data**, we calculated a score, chose a cutoff value, and used these values to segment patients into groups
- To build this scoring system, we:
  - used data from a study in late-stage NSCLC (ATLANTIC)
  - trained a model to predict best overall response (PR/CR) to treatment
  - obtained a formula to calculate predicted probability of response, and used it as the score
- We evaluated OS difference between segmented groups to check performance of our rule
- We then used a second study (study 1108) to independently validate the rule built on ATLANTIC, to show that our proposed algorithm can be used for prediction in future studies

CR, complete response; NSCLC, non-small cell lung cancer; OS, overall survival; PFS, progression-free survival; PR, partial response; SCCHN, squamous cell cancer of the head and neck

## ATLANTIC: phase 2, 3L NSCLC durvalumab monotherapy



- Primary endpoint: ORR
- Follow-up for OS
- First patient in: Q1 2014
- Each arm analyzed separately
- Recruitment into cohorts 1 to 3 closed in Q4 2015

3L, third line; ALK, anaplastic lymphoma kinase; EGFR, epidermal growth factor receptor; IV, intravenous; NSCLC, non-small cell lung cancer; ORR, objective response rate; OS, overall survival; PD, progressive disease; PD-L1, programmed death ligand 1; Q1, first quarter; Q2W, every 2 weeks; Q4, fourth quarter

## Segmentation model

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- To segment patients, we built a model to predict BOR (CR/PR vs others)

*BOR (0/1)  $\approx$  baseline characteristics + early tumor assessment results*

- Baseline characteristics included the following

- Region
- Sex
- Age
- Race
- PD-L1 status
- Histology
- Smoking status
- Performance status
- Cancer stage
- Line of therapy
- Tumor location
- Baseline tumor size

- Early tumor assessments

- We used percent change from baseline at the first two or three follow-up tumor assessments

BOR, best overall response; CR, complete response; PD-L1, programmed death ligand 1;  
PR, partial response

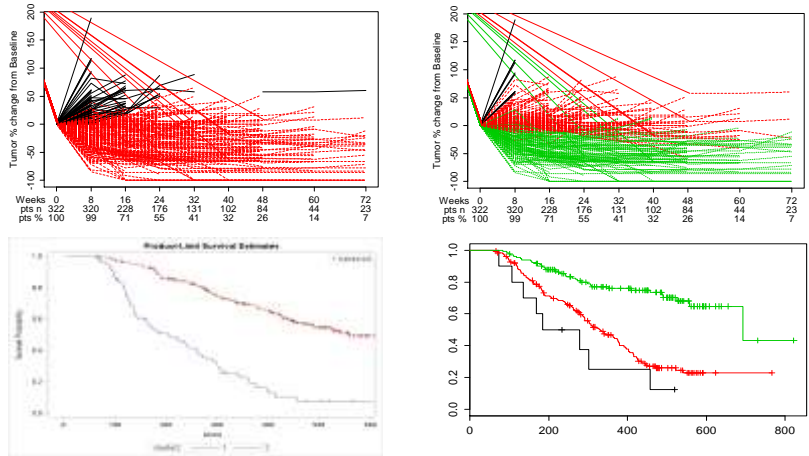
## Tumor kinetics model

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- There are multiple approaches to modeling tumor kinetics
- We considered/compared the following eight approaches
  - Model 1: first principal component score (> 90% of variance)
  - Model 2: tumor size percent change of first 2 or 3 follow-up visits
  - Model 3: 2-cluster membership
  - Model 4: 3-cluster membership
  - Model 5: 4-cluster membership
  - Model 6: 5-cluster membership
  - Model 7: deterministic percent rule (group patients by “ $\geq 2$  visits with  $\geq 10\%$  tumor size reduction”)
  - Model 8: no on-treatment tumor information (to evaluate added value of tumor kinetics)

# Example of clustering tumor growth profile

- A K-means clustering algorithm based on longitudinal tumor assessment was used to group patients into two or three clusters



pts = patients

## The best model?

- Misclassification\* rate was used to evaluate the performance of models

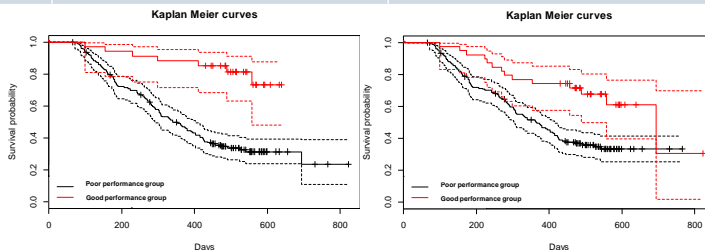
	PCA	% change in tumor	Two clusters	Three clusters	Four clusters	Five clusters	Fixed % rule	No tumor
Using three visits	7.85%	8.38%	16.75%	16.75%	6.28%	6.81%	20.42%	16.75%
Using two visits	9.42%	9.42%	16.75%	19.37%	8.90%	9.95%	19.37%	16.75%

- Using two visits did not result in much worse performance than using three visits, but because we could predict results much earlier, we chose two visits
- The 4-cluster model had the best performance, but this clustering rule is harder to transfer to other studies than other models
- The PCA model is not much worse than the best (4-cluster) model, therefore we decided to use this approach
  - The first PC can be interpreted as the weighted average of tumor percent reductions
- No on-treatment tumor information and the fixed-rule models have the highest misclassification rates

\*Misclassification refers to predicting true responders as non-responders and vice-versa  
 PC, principal component; PCA, principal component analysis

# Comparing observed survival outcomes of predicted groups

	Proposed method		Fixed rule		No tumor	
	Poor performance group (n = 157)	Good performance group (n = 34)	Poor performance group (n = 152)	Good performance group (n = 39)	Poor performance group (n = 191)	Good performance group (n = 0)
Nonresponders	149	10	137	22	159	0
Responders	8	24	15	17	32	0
Median survival (95% CI), days	340 (292–403)	NA (557–NA)	294 (237–409)	769 (682, NA)	410 (340–490)	NA
6-month survival (95% CI), days	0.742 (0.665–0.804)	0.941 (0.785–0.985)	0.740 (0.662–0.803)	0.923 (0.780, 0.975)	0.778 (0.711–0.831)	NA
1-year survival (95% CI), days	0.478 (0.397–0.554)	0.882 (0.716–0.954)	0.501 (0.418–0.578)	0.744 (0.576, 0.853)	0.552 (0.477–0.620)	NA
PH ratio (95% CI) / P value	0.2059 (0.0569–0.4437) / 0.00005		0.4097 (0.2334–0.719) / 0.00187		NA	



Good-performance vs poor-performance groups were based on their cross-validation prediction of responders

CI, confidence interval; NA, not applicable; PH, prediction hazard

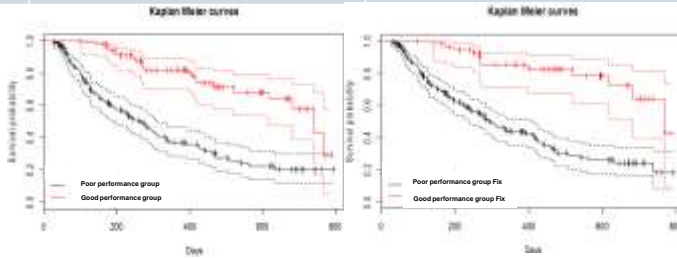
## Patient-segmentation rule

- We refitted the PCA model to full ATLANTIC data to generate a patient-segmentation rule
  - This rule will be used to segment patients in future studies
- The selected variables were:
  - Sex: 0.028 (male response better)
  - Histology group: 0.188 (squamous response better)
  - Smoker group: 0.034 (smoker response better)
  - Line of therapy: -0.176 (earlier-line response better)
  - First PC of tumor percent change from baseline: -0.041 (larger reduction response better)
- Linear combination of the above variables was converted into a probability of response (ie, CR/PR) via a logit link
- A cutoff probability of 0.278 was selected through the second layer of cross-validation and used to segment patients into two groups

CR, complete response; PC, principal component; PCA, principal component analysis; PR, partial response

# Validated patient-segmentation rule in study 1108

	Proposed method		Fixed rule		No tumor	
	Poor performance group (n = 154)	Good performance group (n = 82)	Poor performance group (n = 182)	Good performance group (n = 54)	Poor performance group (n = 236)	Good performance group (n = 0)
Nonresponders	154	34	173	15	188	0
Responders	0	48	9	39	48	0
Median survival (95% CI), days	265 (194–315)	739 (616–NA)	294 (237–409)	769 (682–NA)	425 (310–519)	NA
6-month survival (95% CI), days	0.605 (0.517–0.682)	0.937 (0.855–0.973)	0.653 (0.574–0.720)	0.962 (0.856–0.990)	0.729 (0.664–0.783)	NA
1-year survival (95% CI), days	0.371 (0.282–0.460)	0.819 (0.708–0.891)	0.434 (0.349–0.516)	0.853 (0.715–0.927)	0.542 (0.468–0.611)	NA
PH ratio (95% CI) / P value	0.2637 (0.1661–0.4187) / $1.6 \times 10^{-8}$		0.2168 (0.1185–0.3969) / $7.2 \times 10^{-7}$		NA	

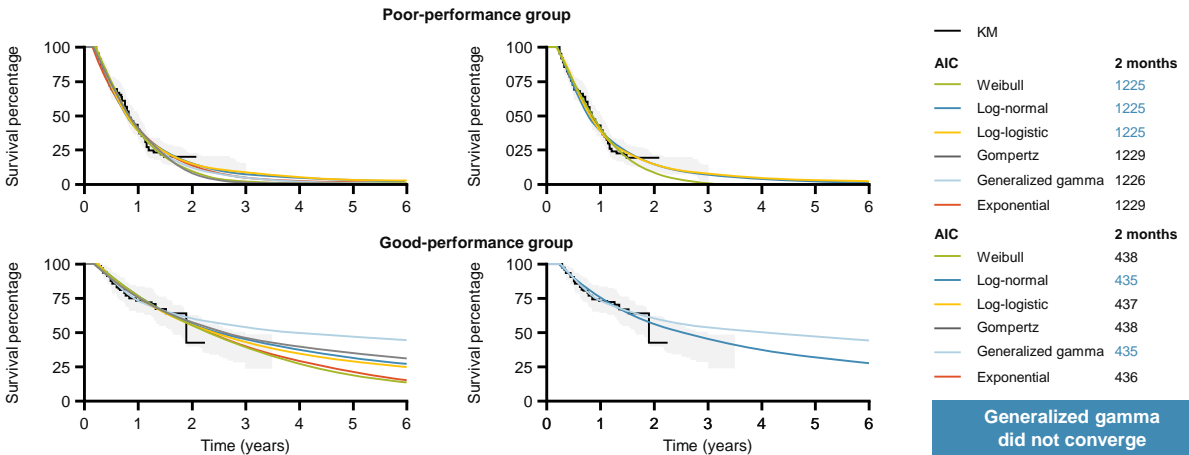


Good-performance vs poor-performance groups were predicted by rule built on the ATLANTIC study

CI, confidence interval; NA, not applicable; PH, prediction hazard

# OS extrapolation using predictive modeling from the ATLANTIC study

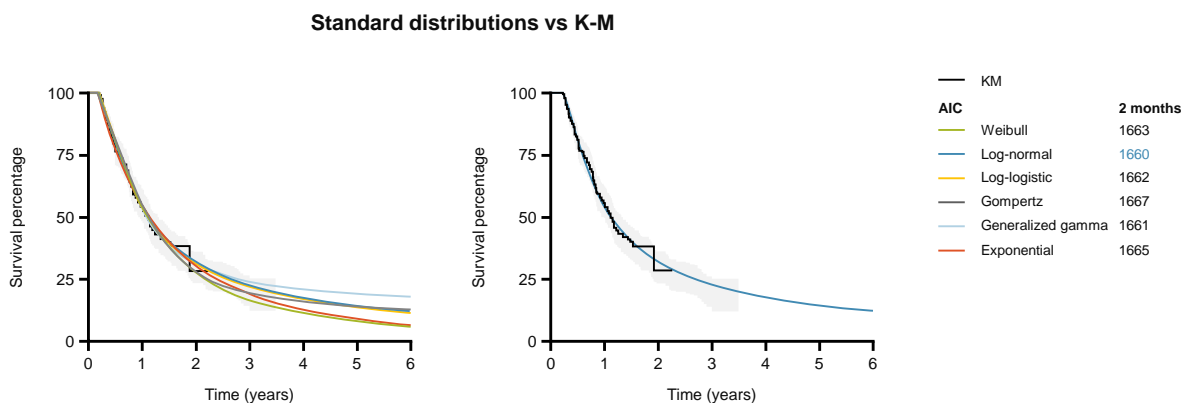
## Standard distributions vs K-M



Generalized gamma did not converge

AIC, Akaike information criterion; K-M, Kaplan-Meier; OS, overall survival

# OS extrapolation using predictive modeling in the overall population



AIC, Akaike information criterion; K-M, Kaplan-Meier; OS, overall survival

## Conclusions

- We built a rule to segment patients into two groups (predicted responders vs nonresponders), using baseline characteristics and early tumor measurements
- We validated our segmentation rule in an independent study
  - The rule shows 100% sensitivity (it detected all true responders)
  - Survival outcomes were significantly different between the two segmented groups
- We hope to extend this approach using data from RCTs to identify predictive models that may help to differentiate between patients receiving I-O and 'non' I-O therapies
- The above approach could also be used in the context of OS extrapolation, instead of using traditional methods to segment patients, such as with landmark models
  - Modeling OS separately in predicted responders and non-responders, allows us to take into consideration the heterogeneity of these populations based on their underlying disease trajectory

I-O, immuno-oncology; RCT, randomized controlled trial; OS, overall survival



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