1	Title: Detecting neuroendocrine prostate cancer through tissue-informed cell-free DNA
2	methylation analysis
3	
4	Authors: Jacob E. Berchuck ^{1,2} *, Sylvan C. Baca ^{1,2} *, Heather M. McClure ^{1,2} *, Keegan
5	Korthauer ^{3,4} , Harrison K. Tsai ⁵ , Pier Vitale Nuzzo ^{1,2} , Kaitlin M. Kelleher ¹ , Monica He ¹ , John A.
6	Steinharter ¹ , Soumya Zacharia ^{1,2} , Sandor Spisak ^{1,2} , Ji-Heui Seo ^{1,2} , Vincenza Conteduca ⁶ , Olivier
7	Elemento ⁷ , Joonghoon Auh ⁷ , Michael Sigouros ⁷ , Eva Corey ⁸ , Michelle S. Hirsch ⁵ , Mary-Ellen
8	Taplin ¹ , Toni K. Choueiri ¹ , Mark M. Pomerantz ^{1,2} , Himisha Beltran ¹ , Matthew L. Freedman ^{1,2}
9	
10	* Equal contribution (J.E.B., S.C.B., H.M.M.)
11	
12	Affiliations:
13	¹ Department of Medical Oncology, Dana-Farber Cancer Institute, Harvard Medical School;
14	Boston, Massachusetts, USA
15	² Center for Functional Cancer Epigenetics, Dana-Farber Cancer Institute; Boston,
16	Massachusetts, USA
17	³ Department of Statistics, University of British Columbia; Vancouver, British Columbia,
18	Canada
19	⁴ BC Children's Hospital Research Institute; Vancouver, British Columbia, Canada
20	⁵ Department of Pathology, Brigham and Women's Hospital and Harvard Medical School;
21	Boston, Massachusetts, USA
22	⁶ Unit of Medical Oncology and Biomolecular Therapy, Department of Medical and Surgical
23	Sciences, University of Foggia; Foggia, Italy

24	⁷ Englander Institute for Precision Medicine, Weill Cornell Medicine, New York, New York,
25	USA
26	⁸ Department of Urology, University of Washington; Seattle, Washington, USA
27	
28	Running Title: NEPC detection using cfDNA
29	
30	Corresponding Author: Matthew L. Freedman, MD; 450 Brookline Ave, Smith 1058, Boston,
31	MA, 02215; Phone: 617-582-8598; Fax: 617-632-2165; <u>mfreedman@partners.org</u>
32	
33	Conflict of Interest Statement: JEB, SCB, and MLF are listed as inventors on patents filed that
34	pertain to the data presented in this manuscript. All other author disclosures are outside the scope
35	of the current manuscript.
36	
37	Key Words: Prostate cancer; Metastatic Castration-Resistant Prostate Cancer; Neuroendocrine

38 Prostate Cancer; Biomarkers; DNA Methylation; Epigenetics

39 ABSTRACT

41	Purpose: Neuroendocrine prostate cancer (NEPC) is a resistance phenotype that emerges in men
42	with metastatic castration-resistant prostate adenocarcinoma (CR-PRAD) and has important
43	clinical implications, but is challenging to detect in practice. Herein, we report a novel tissue-
44	informed epigenetic approach to non-invasively detect NEPC.
45	
46	Experimental Design: We first performed methylated immunoprecipitation and high-throughput
47	sequencing (MeDIP-seq) on a training set of tumors, identified differentially methylated regions
48	between NEPC and CR-PRAD, and built a model to predict the presence of NEPC (termed
49	NEPC Risk Score). We then performed MeDIP-seq on cell-free DNA (cfDNA) from two
50	independent cohorts of men with NEPC or CR-PRAD and assessed the accuracy of the model to
51	predict the presence NEPC.
52	
53	Results: The test cohort comprised cfDNA samples from 48 men, 9 with NEPC and 39 with CR-
54	PRAD. NEPC Risk Scores were significantly higher in men with NEPC than CR-PRAD
55	(P=4.3x10 ⁻⁷) and discriminated between NEPC and CR-PRAD with high accuracy (AUROC
56	0.96). The optimal NEPC Risk Score cut-off demonstrated 100% sensitivity and 90% specificity
57	for detecting NEPC. The independent, multi-institutional validation cohort included cfDNA from
58	53 men, including 12 with NEPC and 41 with CR-PRAD. NEPC Risk Scores were significantly
59	higher in men with NEPC than CR-PRAD ($P=7.5x10^{-12}$) and perfectly discriminated NEPC from
60	CR-PRAD (AUROC 1.0). Applying the pre-defined NEPC Risk Score cut-off to the validation
61	cohort resulted in 100% sensitivity and 95% specificity for detecting NEPC.

62

63 Conclusions: Tissue-informed cfDNA methylation analysis is a promising approach for non64 invasive detection of NEPC in men with advanced prostate cancer.

65

66 STATEMENT OF TRANSLATIONAL RELEVANCE

67

68 Early detection of neuroendocrine prostate (NEPC) is challenging in clinical practice, but has 69 important prognostic and therapeutic implications for men with metastatic castration-resistant 70 prostate cancer (mCRPC). In the largest study to date of cell-free DNA (cfDNA) from men with 71 NEPC, we developed and validated a non-invasive NEPC Risk Score using tissue-informed 72 cfDNA methylation analysis. Applying the NEPC Risk Score to cfDNA from two independent 73 cohorts of men with mCRPC resulted in highly accurate discrimination between men with versus 74 without NEPC. In both cohorts, high NEPC Risk Score was associated with significantly worse 75 overall survival. These data strongly support the clinical utility of this cfDNA methylation-based 76 NEPC Risk Score in men with mCRPC to non-invasively identify those who should be 77 considered for platinum-based chemotherapy or clinical trials of novel NEPC-directed therapies. 78

79 INTRODUCTION

80

Neuroendocrine prostate cancer (NEPC) can arise as a resistance mechanism to androgen
deprivation therapy (ADT) and androgen receptor signaling inhibitors (ARSIs) in men with
metastatic castration-resistant prostate cancer (mCRPC).(1,2) Present in up to 17% of men with
mCRPC, NEPC is associated with poor response to ARSIs and shorter overall survival

85	(OS).(1,3) However, NEPC tumors are more likely to respond to platinum-based chemotherapy
86	and several novel NEPC-directed therapies are in clinical development.(4)
87	
88	The current approach to diagnosing NEPC – performing tissue biopsy for pathologic tumor
89	analysis – has significant shortcomings. There is a lack of consensus pathological criteria for
90	defining NEPC and, due to intra-patient tumor heterogeneity, biopsy samples may not represent
91	a patient's overall disease burden.(5-7) Consequently, NEPC diagnosis is often delayed or
92	missed and reported rates likely underestimate the prevalence of this aggressive disease variant.
93	The lack of a biomarker for early and accurate detection is a significant barrier to improving
94	outcomes for men who develop NEPC.
95	
96	Liquid biopsies are well-suited to address this unmet need. Most clinical cell-free DNA (cfDNA)
97	tests detect somatically acquired tumor mutations or copy number alterations. However, the
98	defining genetic hallmark of NEPC, deleterious alterations in RB1 and/or TP53, are present in
99	more than one-third of castration-resistant prostate adenocarcinoma (CR-PRAD) tumors and thus
100	cannot unambiguously discriminate between the tumor subtypes.(1) In contrast, vast DNA
101	methylation differences exist between NEPC and CR-PRAD.(5) Cell-free methylated DNA
102	immunoprecipitation and high-throughput sequencing (cfMeDIP-seq), a highly sensitive method
103	for genome-wide cfDNA methylation profiling, capable of non-invasive cancer detection and
104	discriminating between tumor types, is well-suited to non-invasively detect NEPC.(8-10)
105	
106	In this manuscript, we evaluate the ability of cfMeDIP-seq to detect NEPC in men with mCRPC.
107	We first perform methylation profiling on a training set of NEPC and PRAD tumors to identify

108	methylation sites enriched in each tumor type. We then establish the ability to implement tissue-
109	informed analysis of cfMeDIP-seq data to detect NEPC in cfDNA from men with NEPC or CR-
110	PRAD. Finally, in an independent cfDNA cohort from men with NEPC or CR-PRAD, we
111	confirm the analytical and clinical validity of this approach for accurate, non-invasive detection
112	of NEPC.
113	
114	MATERIALS AND METHODS
115	
116	Subjects and samples
117	
118	Plasma samples were collected from men with mCRPC diagnosed and treated at the Dana-Farber
119	Cancer Institute (DFCI), Brigham and Women's Hospital, or Weill Cornell Medicine (WCM)
120	between April 2003 and August 2021. Two genitourinary pathologists (H.K.T. and M.S.H.)
121	confirmed the presence of high-grade neuroendocrine carcinoma of prostate origin according to
122	modern conventions based on histologic review of available material, re-interpretation of original
123	reports, and integration of available molecular results.(11) CR-PRAD patients had castration-
124	resistant prostate adenocarcinoma with no pathologic evidence of neuroendocrine differentiation
125	throughout their disease course. All patients provided written informed consent. The use of
126	samples was approved by the DFCI (01-045 and 09-171) and WCM (1305013903). Studies were
127	conducted in accordance with recognized ethical guidelines. The previously-described LuCaP
128	PDXs were derived from resected metastatic prostate cancer with informed consent of patient
129	donors under a protocol approved by the University of Washington Human Subjects Division
130	IRB.(12)

131

132 Sample processing

134	cfDNA samples were processed by the following method. Peripheral blood was collected in
135	EDTA Vacutainer tubes (BD), and processed within 3 hours of collection. Plasma was separated
136	by centrifugation at 2,500 g for 10 minutes, transferred to microcentrifuge tubes, and centrifuged
137	at 2,500 g at room temperature for 10 minutes to remove cellular debris. The supernatant was
138	aliquoted into 1-2 mL aliquots and stored at -80°C until the time of DNA extraction. cfDNA was
139	isolated from 1 mL of plasma, using the Qiagen Circulating Nucleic Acids Kit (Qiagen), eluted
140	in AE buffer, and stored at -80°C. DNA from the LuCaP PDXs was extracted using the DNeasy
141	Blood and Tissue Kit (Qiagen). Genomic DNA was sheared using a Covaris Sonicator E220 and
142	AMPure XP beads (Beckman Coulter) were used to size select 150-250 bp DNA fragments.
143	
144	cfDNA tumor content calculation
145	
146	Low-pass whole genome sequencing (LPWGS) was performed on all cfDNA samples. The
147	ichorCNA R package was used to infer copy number profiles and cfDNA tumor content from
148	read abundance across bins spanning the genome using default parameters.(13)
149	
150	cfMeDIP-seq protocol
151	
152	cfMeDIP-seq was performed using previously published methods.(10) cfDNA library
153	preparation was performed using KAPA HyperPrep Kit (KAPA Biosystems) according to the

154	manufacturer's protocol. We then performed end-repair, A-tailing, and ligation of NEBNext
155	adaptors (NEBNext Multiplex Oligos for Illumina kit, New England BioLabs). Libraries were
156	digested using the USER enzyme (New England BioLabs). λ DNA, consisting of unmethylated
157	and in vitro methylated DNA, was added to prepared libraries to achieve a total amount of 100
158	ng DNA. Methylated and unmethylated Arabidopsis thaliana DNA (Diagenode) was added for
159	quality control. MeDIP was performed using the MagMeDIP kit (Diagenode) following the
160	manufacturer's protocol. Samples were purified using the iPure Kit v2 (Diagenode). Success of
161	the immunoprecipitation was confirmed using qPCR to detect recovery of the spiked-in
162	Arabidopsis thaliana methylated and unmethylated DNA.
163	
164	Next-generation sequencing library construction
165	
166	KAPA HiFi Hotstart ReadyMix (KAPA Biosystems) and NEBNext Multiplex Oligos for
167	Illumina (New England Biolabs) were added to a final concentration of 0.3 uM and libraries
168	were amplified as follows: activation at 95°C for 3 minutes, amplification cycles of 98°C for 20
169	seconds, 65°C for 15 seconds, 72°C for 30 seconds, and a final extension of 72°C for 1 minute.
170	Samples were pooled and sequenced (Novogene Corporation, CA) on Illumina HiSeq 4000 to
171	generate 150 bp paired-end reads.
172	
173	Quality control and processing of sequencing reads
174	
175	After sequencing, the quality and quantity of the raw reads were examined using FastQC version
176	0.11.5 (http://www.bioinformatics.babraham.ac.uk/projects/fastqc) and MultiQC version 1.7.(14)

177	Raw reads were quality and adapter trimmed using Trim Galore! version 0.6.0	
-----	---	--

- 178 (http://www.bioinformatics.babraham.ac.uk/projects/trim_galore/) using default settings in
- paired-end mode. The trimmed reads then were aligned to hg19 using Bowtie2 version 2.3.5.1 in
- paired-end mode and all other settings default.(15) The SAMtools version 1.10 software suite
- 181 was used to convert SAM alignment files to BAM format, sort and index reads, and remove
- 182 duplicates.(16) The R package RSamtools version 2.2.1 was used to calculate the number of
- unique mapped reads. Saturation analyses to evaluate reproducibility of each library were carried
- 184 out using the R Bioconductor package MEDIPS version 1.38.0.(17)
- 185

186 Tissue-informed approach to NEPC detection

187

188 To identify DMRs between NEPC and PRAD tumors, we first binned the genome into 300 base-189 pair windows and tested each window for differential methylation between NEPC and PRAD 190 samples using limma-voom (using R package limma version 3.42.0) on TMM-normalized counts 191 (using R package edgeR version 3.28.0).(18,19) Only bins with a total count above a fixed 192 threshold were tested for differential methylation, where the threshold was set at 20% of the total 193 number of samples across both groups. We restricted our search to bins within annotated CpG 194 islands and FANTOM5 enhancers and excluded regions of high signal or poor 195 mappability.(20,21) We selected DMRs with read enrichment in NEPC compared to PRAD PDXs at FDR-adjusted P< $1.0x10^{-6}$ and \log_2 fold-change >3. We removed windows with peaks in 196 197 MeDIP-seq data from white blood cells (as determined by MACS2, version 2.1.2) to minimize 198 signal from blood cell-derived cfDNA.(22) Using the MeDIPs R package, we calculated a CpG-199 normalized relative methylation scores across 300 bp windows for each cfDNA sample.(17,23)

200	We then summed relative methylation scores in cfDNA at NEPC-enriched PDX DMRs for each
201	sample and normalized this value to the sum of rms values across all 300bp windows. This value
202	was termed "NEPC Methylation Value." The same process was performed for PRAD-enriched
203	PDX DMRs to derive a "PRAD Methylation Value." We then calculated the log ₂ ratio of the
204	NEPC Methylation Value to the PRAD Methylation Value and normalized these values to the
205	median score in cfDNA from eight healthy cancer-free controls. This value was termed the
206	"NEPC Risk Score." This approach is summarized in Fig. 1A.
207	
208	Statistical analysis
209	
210	Comparisons between two groups were calculated using a Wilcoxon rank-sum test. To determine
211	the accuracy of the NEPC Risk Score for discriminating between cfDNA samples from men with
212	NEPC versus CR-PRAD, the AUROC was calculated using JMP version 16. The optimal cut-off
213	for classifying NEPC versus CR-PRAD samples based on NEPC Risk Scores in the cfDNA test
214	cohort was calculated using Youden's index (J = sensitivity + specificity - 1). The optimal cut-
215	off was determined as the point with the maximum index value. OS was defined as time from
216	radiographic evidence of metastatic disease to death. Living patients were censored at the last
217	evaluation. OS was estimated using the Kaplan-Meier method. P-values were calculated using
218	log-rank test. All P-values were two-sided.
219	
220	Data and materials availability
221	

222	The cfMeDIP-seq NGS data for patient samples that support the findings of this study are
223	available upon request from the corresponding author (M.L.F.) to comply with the DFCI ethics
224	regulations to protect patient privacy. All requests for raw and analyzed data will be promptly
225	reviewed by the Belfer Office for Dana-Farber Innovations to verify if the request is subject to
226	any intellectual property or confidentiality obligations. Any data and materials that can be shared
227	will be released via a Data Transfer Agreement. All code used to process the data and carry out
228	the analyses described in the methods is in a publicly available GitHub repository at:
229	https://github.com/scbaca/cfmedip.
230	
231	RESULTS
232	
233	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set
233 234	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set
233 234 235	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in
233 234 235 236	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10)
233 234 235 236 237	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10) However, as men with mCRPC who develop NEPC often have concurrent PRAD, this limits the
233 234 235 236 237 238	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10) However, as men with mCRPC who develop NEPC often have concurrent PRAD, this limits the ability to identify NEPC-specific DMRs directly in cfDNA. To address this unique challenge, we
233 234 235 236 237 238 239	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10) However, as men with mCRPC who develop NEPC often have concurrent PRAD, this limits the ability to identify NEPC-specific DMRs directly in cfDNA. To address this unique challenge, we developed a novel tissue-informed strategy for analyzing cfMeDIP-seq data (Fig. 1A). We first
233 234 235 236 237 238 239 240	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10) However, as men with mCRPC who develop NEPC often have concurrent PRAD, this limits the ability to identify NEPC-specific DMRs directly in cfDNA. To address this unique challenge, we developed a novel tissue-informed strategy for analyzing cfMeDIP-seq data (Fig. 1A). We first performed MeDIP-seq on 29 LuCaP PDXs, including 5 NEPC and 24 PRAD tumors
233 234 235 236 237 238 239 240 241	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10) However, as men with mCRPC who develop NEPC often have concurrent PRAD, this limits the ability to identify NEPC-specific DMRs directly in cfDNA. To address this unique challenge, we developed a novel tissue-informed strategy for analyzing cfMeDIP-seq data (Fig. 1A). We first performed MeDIP-seq on 29 LuCaP PDXs, including 5 NEPC and 24 PRAD tumors (Supplementary Table S1).(12) We chose to analyze PDXs based on recent single-cell analyses
233 234 235 236 237 238 239 240 241 242	Identification of NEPC- and PRAD-enriched DMRs in a tumor training set Prior applications of cfMeDIP-seq for non-invasive cancer detection identified DMRs directly in cfDNA between highly disparate patient groups, such as cancer versus no cancer.(8–10) However, as men with mCRPC who develop NEPC often have concurrent PRAD, this limits the ability to identify NEPC-specific DMRs directly in cfDNA. To address this unique challenge, we developed a novel tissue-informed strategy for analyzing cfMeDIP-seq data (Fig. 1A). We first performed MeDIP-seq on 29 LuCaP PDXs, including 5 NEPC and 24 PRAD tumors (Supplementary Table S1).(12) We chose to analyze PDXs based on recent single-cell analyses of mCRPC clinical biopsy specimens, which revealed significant intra-tumoral heterogeneity,

- which have undergone comprehensive pathologic and molecular characterization, provide a morepure source of NEPC and PRAD tumor cells.(12)
- 246
- 247 Differential methylation analysis of the LuCaP PDXs identified 39,699 NEPC-enriched and
- 248 137,692 PRAD-enriched DMRs (FDR-adjusted P<0.05) (Fig. 1B).(12) To ensure that the PDX
- 249 methylation data is representative of clinical biopsy specimens, we compared the LuCaP-derived
- 250 NEPC- and PRAD-enriched DMRs to DNA methylation data generated from an independent set
- 251 of castration-resistant NEPC and PRAD tumors using reduced-representation bisulfite
- sequencing.(5) We observed a high correlation between NEPC- and PRAD-enriched DMRs from
- the LuCaP PDXs and the clinical biopsy specimens ($\rho=0.73$; P<2.2x10⁻¹⁶) (Fig. 1C).
- 254

255 We then identified a subset of NEPC- and PRAD-enriched DMRs that could be used to non-

invasively detect NEPC. Using a stringent cut-off of FDR-adjusted $P < 1.0 \times 10^{-6}$ and \log_2 fold-

change >3, we identified 432 NEPC-enriched and 1,086 PRAD-enriched DMRs. As the majority

258 of cfDNA is derived from leukocytes, we removed sites that were methylated in WBCs from

age-matched male controls (N=1,165), resulting in a final set of 76 NEPC-enriched and 277

260 PRAD-enriched DMRs. The SPDEF gene highlights the importance of this step. While SPDEF

was methylated in NEPC and unmethylated in PRAD tumors, it is also methylated in WBCs

262 (Fig. 1D). The inability to determine whether a methylated cfDNA fragment at this locus

- 263 originated from NEPC or WBCs renders it uninformative for detecting NEPC and could
- 264 contribute to misclassification. As exemplified in UNC13A, a gene associated with neural
- signaling, the final set of DMRs are methylated in one tumor type and unmethylated in the

266	opposite tumor type and WBCs. Consequently, cfDNA fragments at these loci indicate the
267	presence of NEPC or PRAD.
268	
269	To ensure that the final set of tumor-derived DMRs retained biological relevance, we assessed
270	nearby genes for Gene Ontology (GO) term enrichment.(26) The top GO terms in NEPC-
271	enriched DMRs pertained to neural development and differentiation, whereas PRAD-enriched
272	DMRs related to hormone signaling and epithelial cell differentiation, suggesting that the final
273	set of tumor-derived DMRs reflect the divergent gene regulatory programs of NEPC and PRAD
274	(Fig. 1E).
275	
276	Classification of NEPC and CR-PRAD samples in a cfDNA test cohort
277	
278	To evaluate the ability to accurately detect NEPC using the novel tissue-informed approach, we
279	analyzed a test cohort of plasma cfDNA samples from 56 men with mCRPC, including 11 with
280	NEPC and 45 with CR-PRAD. We first performed LPWGS on all cfDNA samples and
281	calculated tumor content using ichorCNA, an analytical tool that estimates cfDNA tumor
282	fraction based on somatic copy number alterations.(13) Based on the ichorCNA lower limit of
283	detection (3% tumor fraction), 48 (86%) of the 57 cfDNA samples had detectable tumor DNA
284	including 9 (82%) and 39 (87%) of NEPC and CR-PRAD patients, respectively.(13) cfDNA
285	samples with less than 3% tumor content were excluded from methylation analysis
286	(Supplementary Fig. S1). These results compare favorably to a published cfDNA analysis of 269
287	samples from men with metastatic prostate cancer that detected tumor DNA in 83% of samples
288	using LPWGS and hybrid-capture targeted sequencing.(27)

290	Characteristics of men in the cfDNA test cohort at the time of plasma collection are listed in
291	Table 1. Consistent with known decoupling of prostate specific antigen (PSA) from its typical
292	association with disease burden in NEPC, the median PSA was 0.37 for NEPC patients (range
293	0.03-3.7) and 140 for CR-PRAD patients (range 0.79-4305).(11) Median cfDNA tumor content
294	was 15% for men with NEPC (range 5.1-75%) and 21% for those with CR-PRAD (range 3.3-
295	80%) (P=0.89) (Table 1; Supplementary Fig. S2A).
296	
297	To evaluate to the ability to detect NEPC in cfDNA from men with mCRPC, we first performed
298	cfMeDIP-seq on the test cohort samples. We then derived an NEPC Methylation Value and
299	PRAD Methylation Value for each sample by summing the methylated cfDNA fragments at
300	tissue-derived NEPC-enriched and PRAD-enriched DMRs, respectively (Fig. 1A). An NEPC
301	Risk Score was calculated for each sample as the normalized ratio of the NEPC Methylation
302	Value versus the PRAD Methylation Value.
303	
304	We observed significantly higher NEPC Methylation Values in men with NEPC than CR-PRAD
305	(median 8.1x10 ⁻⁶ versus 6.3x10 ⁻⁶ ; P=0.0025) (Fig. 2A). In contrast, PRAD Methylation Values
306	were significantly higher in men with CR-PRAD than NEPC (median 5.4×10^{-5} versus 4.1×10^{-5} ;
307	$P=4.3 \times 10^{-6}$) (Fig. 2B). NEPC Risk Scores were significantly higher in men with NEPC than
308	those with CR-PRAD (median 0.35 versus -0.14; $P=4.3 \times 10^{-7}$) (Fig. 2C). The AUROC for
309	accurate classification of men with NEPC versus CR-PRAD based on NEPC Risk Score was
310	0.96. The optimal NEPC Risk Score cut-off (high >0.15 versus low ≤ 0.15) demonstrated 100%
311	sensitivity and 90% specificity for detecting NEPC. Further, high versus low NEPC Risk Score

312	was associated with significantly shorter OS from the time of metastatic prostate cancer (hazard
313	ratio [HR]=2.5; 95% confidence interval [95%CI]=1.2-4.8; P=0.017) (Fig. 2D). Median OS was
314	32 months shorter for men with high (14 months) versus low (46 months) NEPC Risk Scores.
315	
316	Classification of NEPC and CR-PRAD samples in an independent cfDNA validation cohort
317	
318	To assess the reproducibility of this approach and the NEPC Risk Score cut-off, we identified an
319	independent multi-institutional validation cohort of plasma samples from 73 men with mCRPC
320	at DFCI and WCM, including 16 men with NEPC and 57 with CR-PRAD. cfDNA LPWGS
321	identified tumor DNA in 53 (73%) of samples including 12 (75%) and 48 (72%) of NEPC and
322	CR-PRAD patients, respectively. cfDNA samples with less than 3% tumor content were
323	excluded from methylation analysis (Supplementary Fig. S1). Median cfDNA tumor content was
324	23% for NEPC patients (range 3.4-43%) and 16% for CR-PRAD patients (range 3.8-39%) in the
325	test cohort (P=0.49) (Supplementary Fig. S2B; Table 1). Median PSA was 0.33 (range 0.01-6.23)
326	in men with NEPC versus 112 (range 4.5-1821) in those with CR-PRAD. Differences between
327	men with NEPC and CR-PRAD in the cfDNA validation cohort were similar to those observed
328	in the cfDNA test cohort (Table 1).
329	
330	As we observed in the test cohort, NEPC samples in the cfDNA validation cohort exhibited
331	significantly higher NEPC Methylation Values (median 9.6×10^{-6} versus 6.4×10^{-6} ; P=1.5 x 10^{-4}),
332	lower PRAD Methylation Values (median 4.5x10 ⁻⁵ versus 5.5x10 ⁻⁵ ; P=0.0013), and higher
333	NEPC Risk Scores (median 0.69 versus -0.19; $P=7.5 \times 10^{-12}$) than those with CR-PRAD (Figs.

334 3A-C). The AUROC for accurate classification of men with NEPC versus CR-PRAD based on

335	NEPC Risk Score was 1.0. Applying the NEPC Risk Score cut-off derived in the test cohort
336	(high >0.15 versus low ≤ 0.15) to the cfDNA validation cohort resulted in 100% sensitivity and
337	95% specificity for detecting NEPC. High versus low NEPC Risk Score was associated with
338	significantly shorter OS from the time of metastatic prostate cancer (HR=4.3, 95%CI=2.9-8.9;
339	$P=3.2x10^{-4}$) (Fig. 3D). Median OS was 36 months shorter for men with high (20 months) versus
340	low (56 months) NEPC Risk Scores. Notably, there was no association of cfDNA tumor content
341	with OS across the two cfDNA cohorts (Supplementary Fig. S3), suggesting that the negative
342	correlation between NEPC Risk Score and OS is driven by different tumor biology and not
343	higher disease burden.
344	
345	Patient vignettes highlight NEPC risk factors in misclassified CR-PRAD samples
216	
340	
340	To understand potential factors driving misclassification, we reviewed medical histories for the
340 347 348	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five
347 348 349	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4).
347 348 349 350	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received
 340 347 348 349 350 351 	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received abiraterone, docetaxel, cabazitaxel, and were on enzalutamide at the time of cfDNA collection.
 340 347 348 349 350 351 352 	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received abiraterone, docetaxel, cabazitaxel, and were on enzalutamide at the time of cfDNA collection. The first patient's CT scan six days after cfDNA collection showed marked increase in
 340 347 348 349 350 351 352 353 	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received abiraterone, docetaxel, cabazitaxel, and were on enzalutamide at the time of cfDNA collection. The first patient's CT scan six days after cfDNA collection showed marked increase in metastatic tumor burden, including new liver metastases. He subsequently experienced clinical
 340 347 348 349 350 351 352 353 354 	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received abiraterone, docetaxel, cabazitaxel, and were on enzalutamide at the time of cfDNA collection. The first patient's CT scan six days after cfDNA collection showed marked increase in metastatic tumor burden, including new liver metastases. He subsequently experienced clinical deterioration and died five weeks later. The second patient previously underwent somatic tumor
 340 347 348 349 350 351 352 353 354 355 	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received abiraterone, docetaxel, cabazitaxel, and were on enzalutamide at the time of cfDNA collection. The first patient's CT scan six days after cfDNA collection showed marked increase in metastatic tumor burden, including new liver metastases. He subsequently experienced clinical deterioration and died five weeks later. The second patient previously underwent somatic tumor profiling revealing two-copy <i>RB1</i> deletion. He experienced clinical deterioration and died 8
 340 347 348 349 350 351 352 353 354 355 356 	To understand potential factors driving misclassification, we reviewed medical histories for the six patients with CR-PRAD with NEPC Risk Scores >0.15 across the two cfDNA cohorts. Five of these patients had clinical, radiographic, and genomic features associated with NEPC (Fig. 4). The two patients with the highest NEPC Risk Score (0.50 and 0.36) both previously received abiraterone, docetaxel, cabazitaxel, and were on enzalutamide at the time of cfDNA collection. The first patient's CT scan six days after cfDNA collection showed marked increase in metastatic tumor burden, including new liver metastases. He subsequently experienced clinical deterioration and died five weeks later. The second patient previously underwent somatic tumor profiling revealing two-copy <i>RB1</i> deletion. He experienced clinical deterioration and died 8 weeks after cfDNA collection. The next three patients had all received prior abiraterone and/or

358 underwent tumor biopsy at the time of cfDNA collection showing poorly differentiated 359 carcinoma harboring single-copy RB1 loss and two deleterious TP53 alterations. The second 360 patient (NEPC Risk Score of 0.24) previously received abiraterone and was progressing on 361 enzalutamide at the time of cfDNA collection. Genomic profiling two months earlier showed that 362 the patient's tumor harbored biallelic loss of RB1 and TP53. The third patient (NEPC Risk Score 363 of 0.20) previously received abiraterone and at the time of cfDNA collection was progressing on 364 docetaxel with CT scan showing new liver metastases. He experienced clinical deterioration and 365 died two months later. These hypothesis-generating vignettes suggest the possibility that the 366 cfDNA NEPC Risk Score may identify occult NEPC not detected through routine clinical care. 367 368 Association of the plasma cfDNA methylome with NEPC Risk Score and tumor content 369 370 Prior data suggest that the plasma cfDNA methylome strongly correlates with tumor content in 371 men with metastatic prostate cancer.(28) As such, we sought to understand the association of the 372 cfDNA methylome in this cohort with tumor content. We first performed principal component 373 analysis (PCA) of the genome-wide methylome data (Fig. 5A) and the methylation data at the 374 NEPC- and PRAD-enriched DMRs included in the NEPC Risk Score (Fig. 5B) for the 101 375 cfDNA samples included in the NEPC Risk Score analyses. In the genome-wide data, the first 376 principal component (PC1) is driven by an outlier sample with high CpG enrichment relative to 377 the others. There was otherwise no separation of NEPC and CR-PRAD samples in PC1 and PC2 378 in the genome-wide methylome data (Fig. 5A). However, at the DMR sites, PC1 and PC2 clearly 379 separated NEPC and CR-PRAD samples (Fig. 5B). 380

381 We next quantified the correlation between each of the first 10 PCs with NEPC Risk Score and 382 cfDNA tumor content. For the genome-wide data, not until PC8, which explained 2.2% of variance, was there a robust correlation with NEPC Risk Score ($R^2=0.32$; $P=7.3 \times 10^{-10}$) (Fig. 5C; 383 384 Supplementary Fig. S4A). In contrast, when limiting to the DMRs included in the NEPC Risk Score, PC1 ($R^2=0.34$; $P=1.2x10^{-10}$), which explained 30% of variance, and PC2 ($R^2=0.42$: 385 $P=2.0 \times 10^{-13}$), which explained 8.3% of variance, both demonstrated robust correlation with 386 387 NEPC Risk Score (Fig. 5D; Supplementary Fig. S4B). We then quantified the correlation 388 between the top PCs and cfDNA tumor content. In the genome-wide methylome data, PC2, which explained 4.2% of variance, correlated with cfDNA tumor content ($R^2=0.34$; $P=1.7x10^{-10}$) 389 390 (Fig. 5E; Supplementary Fig. S4A). This result affirms the prior finding that the prostate cancer 391 plasma cfDNA methylome correlates with cfDNA tumor content.(28) When limiting to the DMRs included in the NEPC Risk Score, PC1 ($R^2=0.22$; $P=7.2\times10^{-7}$) and PC2 ($R^2=0.29$; 392 $P=5.1 \times 10^{-9}$) correlated with cfDNA tumor content, though not to the same extent they correlated 393 394 with NEPC Risk Score (Fig. 5F; Supplementary Fig. S4B). 395 396 Finally, we assessed the correlation between NEPC Risk Score and cfDNA tumor content (Fig. 397 5G). Across all NEPC and CR-PRAD cfDNA samples, there was no correlation between NEPC Risk Score and tumor content (R^2 =0.0033; P=0.57); there was also no correlation in the PRAD 398 samples (R²=0.010; P=0.37). NEPC Risk Score and tumor content did significantly correlate in 399 the cfDNA samples from men with NEPC ($R^2=0.24$; P=0.025). Given this association, 400

401 suggesting lower NEPC Risk Scores in men with lower cfDNA tumor content, we evaluated the

402 diagnostic performance of the NEPC Risk Score in the NEPC and CR-PRAD samples across the

403 two cohorts with cfDNA tumor content less than 10%. The NEPC Risk Score in these patients

resulted in an AUROC of 0.93; applying the NEPC Risk Score cut-off of 0.15 resulted in 100%
sensitivity and 82% specificity for detecting NEPC (data not shown).

406

407 **DISCUSSION**

408

409 NEPC is an aggressive, clinically actionable resistance phenotype that can emerge in men with 410 mCRPC. The challenge of identifying NEPC in routine clinical practice leads to delays in 411 diagnosis and underdiagnosis. In the largest study to date of cfDNA from men with NEPC, we 412 present a novel approach for tissue-informed analysis of cfMeDIP-seq data, leading to highly 413 accurate non-invasive detection of NEPC. We first identified methylation sites enriched in a 414 training set of NEPC and PRAD tumors. Tissue-informed methylation analysis of two 415 independent cohorts of cfDNA from men with pathologically confirmed NEPC or CR-PRAD, 416 demonstrated high accuracy (AUROC of 0.96 and 1.0). Importantly, applying a diagnostic cut-417 off derived in the cfDNA test cohort to the independent validation cohort resulted in 100% 418 sensitivity and 95% specificity for detecting NEPC. Finally, in both cfDNA cohorts, a high 419 NEPC Risk Score was associated with significantly shorter OS (HR of 2.5 and 4.3). This work 420 strongly supports the analytical and clinical utility of tissue-informed analysis of cfMeDIP-seq 421 data to non-invasively detect NEPC in men with mCRPC.

422

The current approach for diagnosing NEPC has significant shortcomings that could be overcome with a liquid biopsy. The lack of consensus pathological criteria highlights the advantage of an objective biomarker. Herein, we demonstrated that tissue-informed analysis of cfMeDIP-seq data provides a quantitative readout (NEPC Risk Score) that discriminated between men with NEPC 427 or CR-PRAD with high accuracy in two independent cfDNA cohorts. The ability to apply a 428 diagnostic cut-off from one cfDNA cohort to an independent cohort while maintaining excellent 429 diagnostic accuracy suggests this quantitative approach is robust and reproducible. An additional 430 benefit of a liquid biopsy to detect NEPC is that cfDNA may be more representative of a 431 patient's overall tumor burden than tissue biopsy of a single metastatic focus. (29) Intra-patient 432 tumor heterogeneity is well-established in mCRPC.(6) This is highly relevant in this clinical 433 context, as NEPC often emerges as a treatment-resistant subclone and can be missed due to 434 sampling error with a single tissue biopsy. Future studies analyzing cfDNA from patients 435 undergoing autopsy or correlating cfDNA results with molecular imaging could provide further insight into how representative NEPC Risk Scores are of intra-patient NEPC versus PRAD 436 437 tumor burden. However, we establish is this report that the NEPC Risk Score is a highly accurate 438 quantitative non-invasive biomarker that is highly predictive of the presence or absence of NEPC in men with mCRPC. 439

440

441 Detecting NEPC has important prognostic implications. Compared to men with CR-PRAD, 442 NEPC is associated with shorter OS.(1) Consistent with this known negative prognostic 443 association, we observed that high NEPC Risk Score (relative to the diagnostic cut-off) was 444 associated with significantly shorter OS in two independent cfDNA cohorts. Aggarwal et al 445 reported a HR of 1.8 (95% CI=1.0-3.2) for OS in men with versus without treatment-emergent 446 small-cell neuroendocrine prostate cancer.(1) The HRs for OS in our cohorts were 2.5 447 (95%CI=1.2-4.8) and 4.3 (95%CI=2.0-8.9). The worse prognosis of men with high NEPC Risk 448 Score in our study may reflect differences in patient characteristics. We included only men with 449 morphologic high-grade neuroendocrine carcinoma and not PRAD with expression of

Downloaded from clincancerres.aacrjournals.org on January 18, 2022. © 2021 American Association for Cancer Research.

450 neuroendocrine markers by immunohistochemistry – the latter is not as clearly associated with a
451 virulent clinical course as the former.(11)

452

453 Early and accurate detection of NEPC also has important therapeutic implications. While men 454 with NEPC are characteristically unresponsive to ARSIs, they are more likely to respond to 455 platinum-based chemotherapy.(4) Consequently, NCCN guidelines recommend treatment with 456 platinum chemotherapy combined with etoposide or a taxane.(30) Histology-specific treatment 457 recommendations highlight the immediate clinical actionability of detecting NEPC. With several ongoing clinical trials testing novel therapeutic approaches in men with NEPC, the implications 458 459 of detecting this disease variant will likely increase in the coming years.(31) While the 460 association of the NEPC Risk Score with response to prostate cancer therapy remains to be 461 established, we encourage incorporating cfDNA collection into prospective clinical trials to 462 facilitate future studies to develop and validate non-invasive biomarkers to identify patients 463 likely to benefit from NEPC-directed therapy. 464 465 Successful cfDNA-based biomarkers must be accurate, cost-effective, and practical to implement 466 in clinical practice. Beltran et al previously reported the feasibility of non-invasively detecting 467 NEPC-specific DNA methylation in cfDNA using whole-genome bisulfite sequencing 468 (WGBS).(7) However, test characteristics for distinguishing men with NEPC versus CR-PRAD 469 using this approach were not reported. Compared to WGBS, cfMeDIP-seq has several 470 advantages. The high cost of whole-genome sequencing currently limits the ability to implement 471 WGBS in clinical practice. In contrast, by only sequencing methylated cfDNA, cfMeDIP-seq 472 provides genome-wide methylation data at a fraction of the cost of WGBS. Further, cfMeDIP-

473 seq only requires 5-10 ng of cfDNA, which can be obtained from 1 ml of plasma. While direct
474 comparison of the performance of these approaches will be informative, the low cost, small
475 sample requirement, and high sensitivity highlight advantages of cfMeDIP-seq as the basis for a
476 clinical biomarker.

477

478 The methods presented in this manuscript represent an important advance for developing cfDNA 479 methylation-based clinical biomarkers. Several recent publications highlight advantages of 480 epigenetic compared to genetic liquid biopsy approaches. (32–34) Whereas previous studies 481 performed unsupervised analysis of cfMeDIP-seq data, we developed a novel tissue-informed 482 method, which benefits from the strength of its biological basis. Tissue-informed analysis 483 ensures that the model is built upon molecular features known to be present in and specific to the 484 tumor of interest. This contrasts with the tumor-naïve approach of developing a methylation 485 signature directly in cfDNA (e.g., from individuals with cancer versus without cancer), which 486 risks overfitting due to signal unrelated to cancer (e.g., sex, age, smoking status, comorbid 487 disease, etc). Principal component analysis emphasized the value of this tissue-informed 488 approach. In the genome-wide cfDNA methylome data, not until PC8, which explained only 489 2.2% of variance, did we observe a correlation with the methylation signal that distinguished 490 NEPC from CR-PRAD samples. However, the methylation data at the tissue-derived NEPC- and 491 PRAD-enriched DMRs revealed a strong correlation between NEPC Risk Score and PCs 1 and 492 2, which explained nearly 40% of variance. We believe that the methods presented herein will 493 help facilitate detection of clinically relevant cancer phenotypes. Aberrant DNA methylation is 494 present across tumor types with several clinically actionable subtypes harboring distinct 495 methylation profiles, such as IDH-mutant gliomas and microsatellite instability (MSI) high

uterine and colon cancers.(35–38) As our understanding of clinically-actionable epigeneticallydistinct cancer phenotypes evolves, the methods presented in this manuscript will facilitate noninvasive detection of these tumor subtypes.

499

500 While our results strongly support the feasibility of using cfMeDIP-seq to non-invasively detect 501 NEPC in men with mCRPC, it is appropriate to recognize several potential limitations. First, is 502 the number of patients with NEPC included in the study. The cfDNA test and validation cohorts 503 contained 21 men with NEPC. While this number is small in absolute terms, it represents the 504 largest analysis to date of cfDNA from men with pathologically-confirmed NEPC. While 505 similarly high accuracy was observed across two independent cfDNA cohorts, the reproducibility 506 and clinical validity will benefit from further prospective validation. It is also important to 507 acknowledge that this was a retrospective and heterogeneous cohort, which introduces potential 508 confounding factors, mainly patient selection. This limits our ability to conclusively establish 509 that NEPC Risk Score is associated with inferior clinical outcomes. However, that the NEPC 510 Risk Score performs so well despite the heterogeneity in the cohort speaks to the robustness of 511 the methylation signal and the ability of the assay and methods to detect it. Another limitation is 512 that NEPC patients in this study were limited to men with high-grade neuroendocrine carcinoma 513 and did not include those with PRAD with neuroendocrine differentiation.(11) Thus, we cannot 514 comment on whether the NEPC Risk Score discriminates between these two variants. Likewise, 515 all men in the NEPC group had biopsy-proven high-grade neuroendocrine carcinoma at the time 516 of plasma collection. We did not evaluate plasma samples in men prior to NEPC diagnosis when 517 the relative abundance of NEPC-derived cfDNA may be lower and thus harder to detect. As 518 such, we were not able to establish how early in the disease course this biomarker can detect

519	treatment-emergent NEPC. Finally, as we limited the methylation analysis to men with
520	detectable circulating tumor DNA by ichorCNA, we did not assess how the assay performs in
521	men with very low cfDNA tumor content. More work is needed to fully establish the relationship
522	between NEPC Risk Score with cfDNA tumor content. Several additional questions remain:
523	What is the analytical limit of detection of this cfDNA methylation-based approach for detecting
524	NEPC? What is the optimal timing to evaluate cfDNA in men with mCRPC to identify NEPC?
525	How long before clinical diagnosis can NEPC be detected in cfDNA? Will early detection and
526	initiation of platinum-based chemotherapy improve clinical outcomes for men diagnosed with
527	NEPC? We hope to address these questions in future studies.
528	
529	In summary, we demonstrated the analytical and clinical utility of tissue-informed cfDNA
530	methylation analysis to non-invasively detect NEPC in men with mCRPC. These findings
531	support further studies to establish the prognostic and predictive value of the cfDNA NEPC Risk
532	Score in men with mCRPC. Finally, the novel methods reported in this manuscript are an
533	important step towards broadening the clinical applicability of blood-based epigenomic assays
534	by providing a framework for non-invasive detection of tumor subtypes with distinct DNA
535	methylation profiles.
536	
537	ACKNOWLEDGMENTS: J. Berchuck is supported by the Department of Defense
538	(W81XWH-20-1-0118). S. Baca is supported by a fellowship from the PhRMA Foundation and
539	the Kure It Cancer Research Foundation. K. Korthauer is supported by the Natural Sciences and
540	Engineering Research Council of Canada. Establishment and characterization of the LuCaP PDX
541	models has been supported by the Pacific Northwest Prostate Cancer SPORE (P50CA97186), the

542	Department of Defense Prostate Cancer Biorepository Network (W81XWH-14-2-0183), the		
543	National Cancer Institute P01 CA163227, the Prostate Cancer Foundation, the Institute for		
544	Prostate Cancer Research, and the Richard M. Lucas Foundation. M. Pomerantz, H. Beltran, an		
545	M. Freedman are supported by a DFCI Medical Oncology grant award. H. Beltran is supported		
546	by the National Cancer Institute (5R37CA241486). M. Freedman is supported by the Claudia		
547	Adams Barr Program for Innovative Cancer Research, the H.L. Snyder Medical Research		
548	Foundation, and the Cutler Family Fund for Prevention and Early Detection.		
549			
550	REFERENCES		
551			
552	1. Aggarwal R, Huang J, Alumkal JJ, Zhang L, Feng FY, Thomas GV, et al. Clinical and		
553	Genomic Characterization of Treatment-Emergent Small-Cell Neuroendocrine Prostate		
554	Cancer: A Multi-institutional Prospective Study. J Clin Oncol Off J Am Soc Clin Oncol.		
555	2018;36:2492–503.		
556	2. Abida W, Cyrta J, Heller G, Prandi D, Armenia J, Coleman I, et al. Genomic correlates of		
557	clinical outcome in advanced prostate cancer. Proc Natl Acad Sci U S A. 2019;116:11428		
558	36.		
559	3. Abida W, Cyrta J, Heller G, Prandi D, Armenia J, Coleman I, et al. Genomic correlates of		
560	clinical outcome in advanced prostate cancer. Proc Natl Acad Sci. National Academy of		
561	Sciences; 2019;116:11428–36.		

562	4.	Humeniuk MS, Gupta RT, Healy P, McNamara M, Ramalingam S, Harrison M, et al.
563		Platinum sensitivity in metastatic prostate cancer: does histology matter? Prostate Cancer
564		Prostatic Dis. 2018;21:92–9.
565	5.	Beltran H, Prandi D, Mosquera JM, Benelli M, Puca L, Cyrta J, et al. Divergent clonal
566		evolution of castration-resistant neuroendocrine prostate cancer. Nat Med. 2016;22:298-
567		305.
568	6.	Gundem G, Van Loo P, Kremeyer B, Alexandrov LB, Tubio JMC, Papaemmanuil E, et al.
569		The evolutionary history of lethal metastatic prostate cancer. Nature. 2015;520:353–7.
570	7.	Beltran H, Romanel A, Conteduca V, Casiraghi N, Sigouros M, Franceschini GM, et al.
571		Circulating tumor DNA profile recognizes transformation to castration-resistant
572		neuroendocrine prostate cancer. J Clin Invest. 2020;130:1653-68.
573	8.	Shen SY, Singhania R, Fehringer G, Chakravarthy A, Roehrl MHA, Chadwick D, et al.
574		Sensitive tumour detection and classification using plasma cell-free DNA methylomes.
575		Nature. 2018;563:579–83.
576	9.	Shen SY, Burgener JM, Bratman SV, De Carvalho DD. Preparation of cfMeDIP-seq libraries
577		for methylome profiling of plasma cell-free DNA. Nat Protoc. 2019;14:2749–80.
578	10.	Nuzzo PV, Berchuck JE, Korthauer K, Spisak S, Nassar AH, Abou Alaiwi S, et al. Detection
579		of renal cell carcinoma using plasma and urine cell-free DNA methylomes. Nat Med.
580		2020;26:1041–3.

581	11. Epstein JI, Amin MB, Beltran H, Lotan TL, Mosquera J-M, Reuter VE, et al. Proposed
582	morphologic classification of prostate cancer with neuroendocrine differentiation. Am J
583	Surg Pathol. 2014;38:756–67.
584	12. Nguyen HM, Vessella RL, Morrissey C, Brown LG, Coleman IM, Higano CS, et al. LuCaP
585	Prostate Cancer Patient-Derived Xenografts Reflect the Molecular Heterogeneity of
586	Advanced Disease and Serve as Models for Evaluating Cancer Therapeutics. The
587	Prostate. 2017;77:654–71.
588	13. Adalsteinsson VA, Ha G, Freeman SS, Choudhury AD, Stover DG, Parsons HA, et al.
589	Scalable whole-exome sequencing of cell-free DNA reveals high concordance with
590	metastatic tumors. Nat Commun. 2017;8:1324.
591	14. Ewels P, Magnusson M, Lundin S, Käller M. MultiQC: summarize analysis results for
592	multiple tools and samples in a single report. Bioinforma Oxf Engl. 2016;32:3047–8.
593	15. Langmead B, Salzberg SL. Fast gapped-read alignment with Bowtie 2. Nat Methods.
594	2012;9:357–9.
595	16. Li H, Handsaker B, Wysoker A, Fennell T, Ruan J, Homer N, et al. The Sequence
596	Alignment/Map format and SAMtools. Bioinforma Oxf Engl. 2009;25:2078–9.
597	17. Lienhard M, Grimm C, Morkel M, Herwig R, Chavez L. MEDIPS: genome-wide differential
598	coverage analysis of sequencing data derived from DNA enrichment experiments.
599	Bioinforma Oxf Engl. 2014;30:284–6.

- 600 18. Law CW, Chen Y, Shi W, Smyth GK. voom: Precision weights unlock linear model analysis
- tools for RNA-seq read counts. Genome Biol. 2014;15:R29.
- 602 19. Robinson MD, Oshlack A. A scaling normalization method for differential expression

analysis of RNA-seq data. Genome Biol. 2010;11:R25.

- 604 20. Cavalcante RG, Sartor MA. annotatr: genomic regions in context. Bioinformatics. Oxford
 605 Academic; 2017;33:2381–3.
- 606 21. Amemiya HM, Kundaje A, Boyle AP. The ENCODE Blacklist: Identification of Problematic
 607 Regions of the Genome. Sci Rep. 2019;9:9354.
- 22. Zhang Y, Liu T, Meyer CA, Eeckhoute J, Johnson DS, Bernstein BE, et al. Model-based
 analysis of ChIP-Seq (MACS). Genome Biol. 2008;9:R137.
- 610 23. Pelizzola M, Koga Y, Urban AE, Krauthammer M, Weissman S, Halaban R, et al. MEDME:
- an experimental and analytical methodology for the estimation of DNA methylation levels

based on microarray derived MeDIP-enrichment. Genome Res. 2008;18:1652–9.

- 613 24. Cejas P, Xie Y, Font-Tello A, Lim K, Syamala S, Qiu X, et al. Subtype heterogeneity and
- epigenetic convergence in neuroendocrine prostate cancer. Nat Commun. 2021;12:5775.
- 615 25. Dong B, Miao J, Wang Y, Luo W, Ji Z, Lai H, et al. Single-cell analysis supports a luminal-
- 616 neuroendocrine transdifferentiation in human prostate cancer. Commun Biol. 2020;3:778.
- 617 26. McLean CY, Bristor D, Hiller M, Clarke SL, Schaar BT, Lowe CB, et al. GREAT improves
- 618 functional interpretation of cis-regulatory regions. Nat Biotechnol. 2010;28:495–501.

619	27. Mayrhofer M, De Laere B, Whitington T, Van Oyen P, Ghysel C, Ampe J, et al. Cell-free
620	DNA profiling of metastatic prostate cancer reveals microsatellite instability, structural
621	rearrangements and clonal hematopoiesis. Genome Med. 2018;10:85.
622	28. Wu A, Cremaschi P, Wetterskog D, Conteduca V, Franceschini GM, Kleftogiannis D, et al.
623	Genome-wide plasma DNA methylation features of metastatic prostate cancer. J Clin
624	Invest. American Society for Clinical Investigation; 2020;130:1991–2000.
625	29. Wyatt AW, Annala M, Aggarwal R, Beja K, Feng F, Youngren J, et al. Concordance of
626	Circulating Tumor DNA and Matched Metastatic Tissue Biopsy in Prostate Cancer. JNCI J
627	Natl Cancer Inst [Internet]. 2017 [cited 2019 Aug 11];109. Available from:
628	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6440274/
629	30. NCCN Clinical Practice Guidelines in Oncology: Prostate Cancer (Version 1.2022)
630	[Internet]. 2021. Available from:
631	https://www.nccn.org/professionals/physician_gls/pdf/prostate.pdf
632	31. Berchuck JE, Viscuse PV, Beltran H, Aparicio A. Clinical considerations for the
633	management of androgen indifferent prostate cancer. Prostate Cancer Prostatic Dis. 2021;
634	32. Lasseter K, Nassar AH, Hamieh L, Berchuck JE, Nuzzo PV, Korthauer K, et al. Plasma cell-
635	free DNA variant analysis compared with methylated DNA analysis in renal cell
636	carcinoma. Genet Med Off J Am Coll Med Genet. 2020;22:1366–73.
637	33. Parikh AR, Seventer EEV, Siravegna G, Hartwig AV, Jaimovich A, He Y, et al. Minimal
638	Residual Disease Detection using a Plasma-Only Circulating Tumor DNA Assay in
639	Colorectal Cancer Patients. Clin Cancer Res [Internet]. American Association for Cancer

640	Research; 2021 [cited 2021 May 5]; Available from:	
-----	--	--

- 641 https://clincancerres.aacrjournals.org/content/early/2021/04/28/1078-0432.CCR-21-0410
- 642 34. Liu MC, Oxnard GR, Klein EA, Swanton C, Seiden MV, Liu MC, et al. Sensitive and
- 643 specific multi-cancer detection and localization using methylation signatures in cell-free
- 644 DNA. Ann Oncol. Elsevier; 2020;31:745–59.
- 35. Saghafinia S, Mina M, Riggi N, Hanahan D, Ciriello G. Pan-Cancer Landscape of Aberrant
 DNA Methylation across Human Tumors. Cell Rep. 2018;25:1066-1080.e8.
- 647 36. Noushmehr H, Weisenberger DJ, Diefes K, Phillips HS, Pujara K, Berman BP, et al.
- 648 Identification of a CpG island methylator phenotype that defines a distinct subgroup of
- 649 glioma. Cancer Cell. 2010;17:510–22.
- 650 37. Cancer Genome Atlas Network. Comprehensive molecular characterization of human colon651 and rectal cancer. Nature. 2012;487:330–7.
- 652 38. Cancer Genome Atlas Research Network, Kandoth C, Schultz N, Cherniack AD, Akbani R,
- 653 Liu Y, et al. Integrated genomic characterization of endometrial carcinoma. Nature.
- 654 2013;497:67–73.
- 655
- 656

657 TABLES

658

- **Table 1.** Patient characteristics at the time of cfDNA collection in the test and validation cohorts
- of men with mCRPC.

661

	Test Cohort		Validation Cohort	
	NEPC N = 9	PRAD N = 39	NEPC N = 12	PRAD N = 41
Median cfDNA Tumor Content (Range)	15% (5.1-75%)	21% (3.3-80%)	23% (3.4-43%)	16% (3.8-49%)
Median Age (Range)	72 (60-84)	71 (61-92)	71 (54-91)	70 (49-86)
Median PSA (Range)	0.37 (0.03-3.7)	140 (0.79-4305)	0.33 (0.01-6.23)	112 (4.5-1821)
De Novo NEPC	3 (33%)	N/A	2 (17%)	N/A
Prior Local Therapy	5 (56%)	27 (69%)	5 (42%)	26 (63%)
Prior ADT	4 (44%)	39 (100%)	8 (67%)	41 (100%)
Prior Abiraterone or Enzalutamide	0 (0%)	36 (92%)	4 (33%)	39 (95%)
Prior Docetaxel	2 (22%)	25 (64%)	2 (17%)	35 (85%)
Prior EP Chemotherapy	7 (78%)	0 (0%)	8 (67%)	0 (0%)
Liver Metastases	3 (33%)	15 (38%)	8 (67%)	13 (32%)

662

664 NEPC, neuroendocrine prostate cancer; PRAD, prostate adenocarcinoma; PSA, prostate-specific

antigen; N/A, not applicable; ADT, androgen deprivation therapy; ARSI, androgen receptor

666 signaling inhibitor; EP, etoposide plus platinum.

⁶⁶³ Abbreviations: mCRPC, metastatic castration-resistant prostate cancer; cfDNA, cell-free DNA;

668 FIGURE LEGENDS

669

670	Figure 1. Identification of tumor-derived PRAD-enriched and NEPC-enriched DMRs. A)
671	Overview of the methods used to detect the presence of NEPC based on tissue-informed cfDNA
672	analysis. B) Volcano plot showing differentially methylated regions (DMRs) between PRAD
673	(N=24) and NEPC (N=5) patient-derived xenografts. Red and blue dots represent NEPC-
674	enriched PRAD-enriched (N=137,692) and NEPC-enriched (N=39,699) DMRs, respectively,
675	with FDR-adjusted P<0.05. C) Correlation between tumor-derived DMRs with differentially
676	methylated nucleotides in reduced representation bisulfite sequencing (RRBS) data from CR-
677	PRAD and NEPC tumors.(5) D) Tracks depict methylation at the SPDEF gene and UNC13A
678	gene determined by MeDIP-seq in PRAD tumors, NEPC tumors, and white blood cells (WBCs).
679	E) The top 5 gene ontology (GO) enrichment terms for PRAD-enriched and NEPC-enriched
680	DMRs after removing sites with DNA methylation in WBCs.
681	
682	Figure 2. Classification of NEPC and PRAD samples in the cfDNA test cohort. NEPC
683	Methylation Values (A), PRAD Methylation Values (B), and NEPC Risk Scores (C) in cfDNA
684	samples from men with PRAD or NEPC in the test cohort. P-Values calculated using a two-sided
685	Wilcoxon rank-sum test. Optimal cut-off (indicated by dotted gray line) was determined in this
686	cohort using Youden's J statistic. D) Kaplan-Meier curve for overall survival (OS) from the time
687	of metastatic disease for men with high (>0.15) versus low (≤0.15) NEPC Risk Score relative to
688	the cut-off.

690	Figure 3. Classification of NEPC and PRAD samples in the cfDNA validation cohort. NEPC
691	Methylation Values (A), PRAD Methylation Values (B), and NEPC Risk Scores (C) in cfDNA
692	samples from men with NEPC or PRAD in the validation cohort. P-Values calculated using a
693	two-sided Wilcoxon rank-sum test. The optimal NEPC Risk Score cut-off determined in the
694	independent cfDNA test cohort is indicated by dotted gray line. D) Kaplan-Meier curve for
695	overall survival (OS) from the time of metastatic disease for men with high (>0.15) versus low
696	(≤0.15) NEPC Risk Score relative to the cut-off determined in the independent cfDNA test
697	cohort.
698	
699	Figure 4. cfDNA from men with CR-PRAD with high NEPC Risk Scores display clinical and
700	genomic features of NEPC.
701	
702	Figure 5. Association of the plasma cfDNA methylome with NEPC Risk Score and tumor
703	content. A) Principal component analysis (PCA) of the genome-wide methylome for 101 plasma
704	cfDNA samples from men with CR-PRAD or NEPC. B) PCA of the 101 plasma cfDNA samples
705	limiting to the NEPC- and PRAD-enriched DMRs included in the NEPC Risk Score. Correlation
706	between NEPC Risk Score with the top 10 principal components (PCs) for the cfDNA genome-
707	wide methylome data (C) and restricted to the DMR sites (D). Correlation between cfDNA
708	tumor content with the top 10 PCs for the cfDNA genome-wide methylome data (E) and
709	restricted to the DMR sites (F). Correlation between NEPC Risk Score and each PC was
710	measured using the coefficient of determination (R^2). * P<0.05; ** P<1x10 ⁻⁶ . G) Correlation
711	between NEPC Risk Score and tumor content for the 101 cfDNA samples from men with NEPC

- and CR-PRAD. Dotted lines show the linear regression for the NEPC samples (red), CR-PRAD
- 713 samples (blue), and all samples (purple).

Figure 1

Author Manuscript Published OnlineFirst on December 14, 2021; DOI: 10.1158/1078-0432.CCR-21-3762 Author manuscripts have been peer reviewed and accepted for publication but have not yet been edited.



E

Top GO Terms in PRAD-enriched DMRs



Top GO Terms in NEPC-enriched DMRs







Author Manuscript Published OnlineFirst on December 14, 2021; DOI: 10.1158/1078-0432.CCR-21-3762 Author manuscripts have been peer reviewed and accepted for publication but have not yet been edited.





Author Manuscript Published OnlineFirst on December 14, 2021; DOI: 10.1158/1078-0432.CCR-21-3762 Author manuscripts have been peer reviewed and accepted for publication but have not yet been edited.





Author Manuscript Published OnlineFirst on December 14, 2021; DOI: 10.1158/1078-0432.CCR-21-3762 Author manuscripts have been peer reviewed and accepted for publication but have not yet been edited.



Prior abiraterone, docetaxel, cabazitaxel, progressing on enzalutamide at the time of cfDNA collection. CT scan / showed **new liver metastases**. He experienced clinical deterioration and **died 5 weeks later**.

Prior abiraterone, docetaxel, cabazitaxel, progressing on enzalutamide at the time of cfDNA collection. Prior somatic tumor profiling revealed **two-copy** *RB1* loss. He experienced clinical deterioration and **died 8 weeks later**.

Prior enzalutamide, progressing on abiraterone at the time of cfDNA collection. Tumor biopsy at the time of cfDNA collection showed poorly differentiated carcinoma harboring two-copy *TP53* loss and one-copy *RB1* loss.

Prior abiraterone, progressing on enzalutamide at the time of cfDNA collection. Somatic tumor profiling two months earlier revealed two-copy *RB1* loss and two-copy *TP53* loss.

Prior abiraterone, progressing on docetaxel at the time of cfDNA collection. CT scan showed **new liver metastases**. He experienced clinical deterioration and **died 8 weeks later**. Figure 5

Author Manuscript Published OnlineFirst on December 14, 2021; DOI: 10.1158/1078-0432.CCR-21-3762 Author manuscripts have been peer reviewed and accepted for publication but have not yet been edited.



Downloaded from cincancerres.aacrjournals.org on January 18, 2022. © 2021 American Association for Cancer cfDNA Tumor Content Research.



Clinical Cancer Research

Detecting neuroendocrine prostate cancer through tissue-informed cell-free DNA methylation analysis

Jacob E. Berchuck, Sylvan C. Baca, Heather M. McClure, et al.

Clin Cancer Res Published OnlineFirst December 14, 2021.



E-mail alerts	Sign up to receive free email-alerts related to this article or journal.
Reprints and Subscriptions	To order reprints of this article or to subscribe to the journal, contact the AACR Publications Department at pubs@aacr.org.
Permissions	To request permission to re-use all or part of this article, use this link http://clincancerres.aacrjournals.org/content/early/2021/12/13/1078-0432.CCR-21-3762. Click on "Request Permissions" which will take you to the Copyright Clearance Center's (CCC) Rightslink site.