Graphical Abstract

Multiple Epithelial Cancers

Small Cell Neuroendocrine Cancer (SCNC)

SCNC subtypes

PGC-1α

ASCL1

SCNC subtypes	POU2F3/ASCL2	ASCL1
Metabolic Heterogeneity	↓ PGC-1α	↑ PGC-1α
	↓ OXPHOS	↑ OXPHOS
	↓ Metabolic Plasticity	↑ Metabolic Plasticity
Metabolic Vulnerability	↑↑ Sensitivity to OXPHOS Inhibition	↑ Sensitivity to OXPHOS Inhibition

PGC-1α drives small cell neuroendocrine cancer progression towards an ASCL1-expressing subtype with increased mitochondrial capacity

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SUMMARY

Adenocarcinomas from multiple tissues can converge to treatment-resistant small cell neuroendocrine (SCN) cancers comprised of ASCL1, POU2F3, NEUROD1, and YAP1 subtypes. We investigated how mitochondrial metabolism influences SCN cancer (SCNC) progression. Extensive bioinformatics analyses encompassing thousands of patient tumors and human cancer cell lines uncovered enhanced expression of PGC-1α, a potent regulator of mitochondrial oxidative phosphorylation (OXPHOS), across several SCNC types. PGC-1α correlated tightly with increased expression of the lineage marker ASCL1 through a positive feedback mechanism. Analyses using a human prostate tissue-based SCN transformation system showed that the ASCL1 subtype has heightened PGC-1α expression and OXPHOS activity. PGC-1α inhibition diminished OXPHOS, reduced SCNC cell proliferation, and blocked SCN prostate tumor formation. PGC-1α overexpression enhanced OXPHOS, tripled the SCN prostate tumor formation rate, and promoted commitment to the ASCL1 lineage. These findings reveal the metabolic heterogeneity among SCNC subtypes and identify PGC-1α-induced OXPHOS as a regulator of SCNC lineage plasticity.

INTRODUCTION

Epithelial cancers from various tissues, including the prostate, lung, and bladder, can converge to an aggressive small cell neuroendocrine (SCN) phenotype under targeted treatments[1–3]. Small cell neuroendocrine cancers (SCNCs) are classified as high-grade, poorly differentiated small cell carcinomas that commonly express neuroendocrine markers like chromogranin A (CHGA), neural cell adhesion molecule 1 (NCAM1), and synaptophysin (SYP)[4]. The most common type of SCNC, small cell lung cancer (SCLC), represents around 14% of all lung cancer diagnoses. Globally, about 250,000 individuals are diagnosed with SCLC annually, with roughly 200,000 of these patients succumbing to the disease each year. Although de novo neuroendocrine prostate cancer is rare (<1% of cases), the prevalence of treatment-induced SCN prostate cancer is increasing, likely due to resistance mechanisms triggered by androgen deprivation therapy (ADT)[5,6]. This treatment-induced form of prostate cancer accounts for about 10-40% of all ADT-insensitive, castration-resistant prostate cancer (CRPC) cases.

With a limited long-term effectiveness of current chemotherapy strategies[7] indicated by a dismal median

survival rate between 7-16 months[8], there is an urgent need for alternative treatment strategies.

SCNCs were traditionally seen as a uniform group of cancers but are now understood to include

multiple subtypes. These subtypes, defined by their prominent expression of lineage-specific molecular

markers, showcase the diversity within SCNCs. This is best exemplified in SCLC, which is categorized

into ASCL1, NEUROD1, POU2F3, and YAP1 subtypes[9,10]. Recent studies have identified corresponding

subtypes in SCN prostate cancer, including ASCL1, POU2F3/ASCL2, and NEUROD1[11–13]. A growing

body of research across numerous SCNC models has highlighted the plastic nature of differentiation

towards and between these subtypes[9,10,14,15], a feature that likely contributes to treatment resistance.

Complementing the molecular heterogeneity within SCNCs, recent studies have begun to

highlight the metabolic diversity across different SCLC subtypes[16–20]. Notably, a correlation has been

observed between ASCL1 expression levels and a dependence on inosine monophosphate

dehydrogenase, a key enzyme in guanosine biosynthesis critical for normal metabolic functions[16]. These

insights raise the possibility that metabolic reprogramming might regulate lineage plasticity in SCNCs.

Indeed, metabolic reprogramming not only influences cell fate decisions[21] but is also orchestrated by

oncogenes to regulate these decisions[22]. These observations highlight the intimate interplay between

cancer metabolism and lineage plasticity. Specifically, SCN-associated oncogenes such as MYC[23–27],

AKT[28,29], TP53[30,31], and RB1[32–34], regulate metabolic pathways individually, but their collective impact on

metabolic reprogramming and lineage determination during SCNC remains unclear.

A key aspect of cancer cell metabolic reprogramming is the shift towards aerobic glycolysis (also

known as the Warburg effect) characterized by an increased rate of glucose consumption and lactate

secretion, even in the presence of ample oxygen[35–37]. This seminal discovery made nearly a century ago

by Otto Warburg led to a longstanding belief that cancer cells have dysfunctional mitochondria. However,

recent studies have countered this perspective, showing that many cancers actually have functional

mitochondria fully capable of processing fuels via the tricarboxylic acid (TCA) cycle to support oxidative

phosphorylation (OXPHOS)[38]. In fact, some cancers have a heightened reliance on OXPHOS[39,40], which

is sometimes linked with therapy resistance[41–46]. This emerging understanding has sparked significant

interest in OXPHOS inhibitors as promising candidates for cancer therapy[47–49].

Increased aerobic glycolysis has been observed in SCN prostate cancer[50], but the specific role of

OXPHOS in SCN transformation and lineage plasticity remains to be unraveled. Thus, we reasoned that

investigating OXPHOS in SCNCs could unveil new insights into SCNC biology. To explore the influence

of mitochondrial function on SCNC development, we focused on peroxisome proliferator-activated

receptor gamma coactivator 1-alpha (PGC-1α)[51], a transcriptional co-activator widely recognized as a

potent regulator of mitochondrial biogenesis and OXPHOS. Originally identified for its role in cold-induced

adaptive thermogenesis through the regulation of OXPHOS genes[52], PGC-1α has since been implicated

in metabolic reprogramming during cancer development, demonstrating robust but varied effects across

cancer types[53]. In prostate cancer, it has been found to support the growth of localized, androgen-

dependent tumors[54,55] while restraining the progression of androgen-independent, metastatic forms[56–58].

In melanoma, PGC-1α is associated with tumors that exhibit enhanced mitochondrial function[59] and a

reduced metastatic potential[60]. It suppresses metastasis in non-small cell lung cancer (NSCLC)[61], but

promotes metastasis in other cancer models[62]. The specific impact of PGC-1α on SCNC has yet to be

determined.

To investigate the role of PGC-1α in regulating SCNC development, we performed an integrated

computational and functional investigation. Bioinformatics analyses of 10,529 patient tumors and 1,466

human cancer cell lines were performed, followed by functional and mechanistic analyses using a human

prostate tissue-derived SCN transformation system, referred to as PARCB[2,3,13]. This system enables the

transformation of normal human lung epithelial cells, prostate epithelial cells, or bladder urothelial cells

into SCNC via transduction with an oncogene cocktail abbreviated as PARCB (T<u>P</u>53DN, myr-<u>A</u>KT,

sh<u>R</u>B1, <u>c</u>-MYC, and <u>B</u>CL2). This model generates two distinct tumor lineages characterized by either

stem-like (POU2F3/ASCL2 subtype) or neuroendocrine features (ASCL1 subtype) that closely resemble

the POU2F3 and ASCL1 subtypes seen in clinical SCNCs[13]. Here, we reveal the metabolic heterogeneity

between SCNC subtypes and identify PGC-1α as a driver of the ASCL1 lineage.

RESULTS

Elevated PGC-1α in clinical SCNC correlates with increased ASCL1 expression and neuroendocrine differentiation.

To investigate the role of PGC-1α in SCNCs, we conducted bioinformatics analyses in a wide range of human cancer cell lines, human primary tumors, and clinical SCN datasets. First, a co-expression analysis was conducted on PGC-1α against the four SCNC lineage markers—ASCL1, POU2F3, NEUROD1, and YAP1—across all 1,466 human cancer cell lines from the Cancer Cell Line Encyclopedia (CCLE). PGC-1α shows no correlation with POU2F3, NEUROD1, or YAP1 (**Figure S1A**). Conversely, PGC-1α exhibits a positive correlation with ASCL1, a pioneer transcription factor that is essential for neuronal commitment and SCNC progression[63–65]. Notably, a subpopulation of cell lines with high ASCL1 expression has a co-upregulation of PGC-1α (**Figure 1A**). This subpopulation is comprised predominantly of two neuroendocrine cancer cell types: small cell lung cancer (SCLC) and neuroblastoma (34/43, 79%) (**Figure 1A**). Consistently, PGC-1α expression is elevated in SCLC and neuroblastoma cell lines compared with NSCLC (**Figure S1B**). To check whether the subpopulation of cells with PGC-1α/ASCL1-High expression have increased SCN differentiation, we applied a well-established SCN score derived from a pan-cancer transcriptomic analysis[1]. A higher SCN score indicates a more SCN-like phenotype (see Methods section for more details). Cell lines with high PGC-1α and ASCL1 expression have a higher SCN score compared with the rest of the samples, indicating heightened neuroendocrine differentiation (**Figure 1B**). Together, these data suggest a link between PGC-1α, ASCL1, and SCN differentiation.

To check whether PGC-1α expression correlates with ASCL1 and SCN differentiation in patient tumors, we analyzed 10,529 solid tumors from The Cancer Genome Atlas (TCGA)[66]. Consistent with the CCLE cancer cell lines, a subpopulation of patient tumors has elevations in both PGC-1α and ASCL1 expression (**Figure S1C**), and a higher SCN score (**Figure 1C**). Next, the analysis was extended to include clinical SCN samples. Clinical datasets were mined from multiple cancers, including clinical lung adenocarcinoma (LUAD), castration resistant prostate cancer (CRPC), SCN prostate cancer (NEPC), and SCLC. As in the human cancer cell lines (from the CCLE) and patient tumors (from the TCGA), the

majority of clinical samples with increased ASCL1 expression have high PGC-1α expression (**Figure 1D)**. Most patient samples with high PGC-1α and ASCL1 expression (56/83; 67%) in this dataset were neuroendocrine cancers and have a higher SCN score (**Figure 1D, right panel**). Consistent with these observations, PGC-1α expression is increased in SCN prostate cancer compared with castration resistant prostate cancer (CRPC)[67] and in SCLC[68] compared with NSCLC[66] (**Figure 1E**). Of note, the increased PGC-1α expression in SCLC is largely attributable to a neuroendocrine subtype expressing ASCL1 (SCLC-A), further corroborating the link between PGC-1α and ASCL1 (**Figure 1E, right panel**).

Epithelial ovarian cancers, particularly high-grade serous ovarian carcinomas (HGSOC), share genomic alterations with neuroendocrine tumors including mutations in TP53, loss of RB1, and amplification of MYC[69]. We therefore examined expression of PGC-1α and its correlation with ASCL1 in a cohort of patients with a diagnosis of HGSOC. A positive correlation between PGC-1α and ASCL1 is also observed in these samples (**Figure S1D**), highlighting a consistent link across multiple clinical sample types.

Given the contribution of ADT to SCN prostate cancer progression[5,6], we next examined the effect of ADT on the PGC-1α expression in prostate cancer (**Figure 1F**). A clinical transcriptomic dataset was utilized in which tumors were biopsied from the same prostate cancer patients before and after ADT with enzalutamide, a potent and selective antagonist of the androgen receptor[70]. ADT-treated tumors exhibit increased PGC-1α expression, which is positively correlated with ASCL1 (**Figure 1F**). To identify enriched pathways upon ADT treatment, we performed gene set enrichment analysis (GSEA) on patient samples before and after ADT. This analysis revealed OXPHOS as a top enriched pathway in post-ADT tumors (**Figure 1G**). As expected, the Androgen Response pathway is a top downregulated pathway in patient tumors post-ADT (**Figure 1G**). Collectively, these data indicate that PGC-1α expression is upregulated in multiple SCNC types and uncover a link between PGC-1α, ASCL1, and SCN differentiation.

Enhanced PGC-1α expression and OXPHOS activity in SCN prostate cancer within the ASCL1 tumor subtype.

Having established a link between PGC-1α and ASCL1 in multiple clinical SCNCs, we next sought

to investigate the functional role of PGC-1α in specific SCNCs subtypes. With this goal in mind, we utilized

our human tissue-derived PARCB-induced SCN transformation model[13]. This model produces ASCL1

and POU2F3/ASCL2 subtypes, closely resembling clinical SCLC and SCN prostate cancer subtypes

(**Figure 2A**). To determine if PGC-1α is linked to the ASCL1 subtype in the PARCB model, we conducted

a co-expression analysis across all PARCB time course samples. This analysis revealed a tight and

positive correlation between PGC-1α and ASCL1, exclusively observing the highest expression of both

genes in the ASCL1 subtype (**Figure 2B**). Corroborating this observation, PGC-1α expression markedly

increased in five out of ten PARCB tumor series derived from distinct donor tissue series (**Figure 2C**).

Moreover, across all the patient series, the ASCL1 neuroendocrine subtype demonstrated a 16-fold

higher expression of PGC-1α compared with the POU2F3/ASCL2 subtype (**Figure 2D)**. To check

whether PGC-1α and ASCL1 are co-expressed at the single cell level, we examined single-cell RNA-

sequencing (scRNA-seq) from the same PARCB time course dataset[13]. The analysis revealed that high

PGC-1α expression was almost exclusively associated with ASCL1, while it was absent in cells

expressing POU2F3 or ASCL2 (**Figure S2**). Collectively, these data indicate increased PGC-1α

expression in the PARCB model's ASCL1 subtype, which aligns with the bioinformatics analyses in

patient tumors and clinical datasets described in Figure 1.

Building on our findings that PGC-1α expression is elevated in the ASCL1 tumor subtype, we

further investigated the regulatory mechanisms underlying this phenomenon. Specifically, we aimed to

determine if transcription factors (TFs) co-activated by PGC-1α are more accessible in the ASCL1

subtype than in the POU2F3/ASCL2 subtype. To this end, we employed Hypergeometric Optimization of

Motif EnRichment (HOMER) analysis was performed to compare the accessible peaks in both tumor

subtypes. There was a notable enrichment of TFs co-activated by PGC-1α in the ASCL1 tumor subtype,

several of which were among the most significantly enriched (**Figure 2E**). This enrichment suggests

enhanced PGC-1α-induced TF signaling in the ASCL1 subtype.

To define the transcriptional changes associated with the development of the ASCL1 subtype in

an unbiased manner, GSEA was performed in tumors of the ASCL1 subtype versus all the other stages

of PARCB transformation (**Figure 2F**). Consistent with their high PGC-1α expression and TF signaling,

ASCL1 tumors had pronounced upregulation of oxidative phosphorylation (OXPHOS) genes (**Figure 2F**),

indicating increased mitochondrial biogenesis and/or activity. To determine whether the increased

OXPHOS expression translated to higher OXPHOS activity, we performed Seahorse respirometry. This

plate-based extracellular flux analysis utilizes multiple inhibitors targeting different components of the

OXPHOS machinery, providing a detailed functional profile of OXPHOS activity[71]. Seahorse respirometry

revealed that PARCB-ASCL1 tumor-derived cell lines exhibited a marked increase in basal and maximal

oxygen consumption rates compared with the POU2F3/ASCL2 subtype (**Figure 2G**), indicating increased

OXPHOS activity. Furthermore, the ASCL1 tumor subtype had higher expression of both subunits of the

mitochondrial pyruvate carrier (MPC) (**Figure 2H**), an obligate heterodimer in the mitochondrial inner

membrane that allows entry of pyruvate into the mitochondrion[72]. These findings demonstrate that the

ASCL1 subtype exhibits enhanced PGC-1α expression and OXPHOS activity.

<u>PGC-1α inhibition blunts OXPHOS, reduces the growth of SCNC cell lines, and blocks SCN prostate</u>

<u>tumor formation.</u>

Considering the high PGC-1α expression and high OXPHOS activity in the PARCB ASCL1

subtype described in Figure 2, we next asked whether PGC-1α is important for PARCB tumor

progression. To investigate, PGC-1α was inhibited during PARCB prostate transformation using shRNA

interference (**Figure 3A**). PGC-1α inhibition was verified using RT-qPCR in PARCB organoids before

xenografting into immunocompromised mice for tumor formation (**Figure 3B**). Strikingly, PGC-1α

inhibition blocked PARCB tumor growth, underscoring its requirement for PARCB prostate tumor

initiation.

Since PARCB tumors could not form under PGC-1α inhibition, we explored its role in maintaining

PARCB-derived ASCL1 and POU2F3/ASCL2 prostate cancer cell lines. PGC-1α inhibition reduced the

proliferation of both subtypes and the response was unexpectedly more pronounced in the POU2F3

subtype (**Figures 3C and 3D**). Next, we examined whether pharmacological inhibition of PGC-1α

similarly affects cell proliferation. Post-translational modifications are recognized as key regulators of

PGC-1α activity[73,74]. Among these, acetylation of lysine residues is one of the most well-characterized

modifications impacting PGC-1α activity. A recent high-throughput screen identified a small molecule

inhibitor called SR-18292 that increases PGC-1α lysine acetylation and inhibits PGC-1α activity by

blocking its interaction with HNF4A[75]. As with genetic inhibition, SR-18292 treatment suppressed growth

in both ASCL1 and POU2F3/ASCL2 subtypes, with a stronger effect on the POU2F3ASCL2 subtype

(**Figure S3**).

To determine whether the effect of PGC-1α inhibition extends beyond the PARCB-derived cell

lines, we tested patient-derived SCN prostate and lung cancer cell lines. PGC-1α inhibition reduced the

growth of the sole patient-derived SCN prostate cancer cell line, NCI-H660 (**Figure 3E**). Similarly,

analysis of PGC-1α inhibition in the Cancer Dependency Map (DepMap)[76] revealed a stronger anti-

proliferative effect in SCLC compared with NSCLC (**Figure 3F**). Taken together, these findings indicate

that PGC-1α inhibition blunts the growth of multiple SCNC types.

We next sought to understand the functional mechanism behind PGC-1α inhibition's impact on

SCNC cell line growth and PARCB tumor suppression. Accordingly, we inhibited PGC-1α in ASCL1 and

POU2F3/ASCL2 cell lines using shRNA and performed Seahorse respirometry to examine the effect on

mitochondrial function. PGC-1α inhibition downregulated basal and maximal respiration in both the

ASCL1 and POU2F3/ASCL2 subtypes (**Figure 3G**), highlighting the importance of PGC-1α in maintaining

OXPHOS activity across both subtypes. These findings collectively suggest that PGC-1α is essential for

the initiation of PARCB prostate tumors and sustaining OXPHOS and proliferation of cultured SCNC cell

lines.

<u>OXPHOS inhibition blunts SCN prostate and lung cancer cell line proliferation.</u>

Because PGC-1α inhibition blunted OXPHOS and reduced the growth of multiple cultured SCNC

cell types, we next asked whether OXPHOS specifically is required for the growth of SCNC cell lines.

First, PARCB cell lines derived from the ASCL1 and POU2F3/ASCL2 tumor subtypes were treated with

IACS-010759, a clinical-grade respiratory chain complex I inhibitor. This treatment abolished OXPHOS

in cell lines derived from both subtypes (**Figure 4A**). To confirm the inhibitor's specificity and ensure that

the observed effects were directly due to complex I inhibition, NDI1, a yeast complex I[48,77] was overexpressed concurrently with complex I inhibition. NDI1 overexpressed fully rescued the OXPHOS inhibition caused by IACS-010759 (**Figure 4A**). Interestingly, NDI1 overexpression boosted the oxygen consumption rate (OCR) above baseline levels in the ASCL1 subtype (**Figure 4A**), suggesting that this subtype not only has increased baseline levels of OXPHOS activity but may also have higher metabolic plasticity.

Having verified that IACS-010759 blocks OXPHOS in these SCNC cell lines, we next asked whether its treatment would reduce their proliferation in culture. In line with PGC-1α inhibition experiments described in Figure 3, IACS-010759 treatment reduced proliferation of cell lines derived from both subtypes, with a more pronounced effect in the POU2F3/ASCL2 subtype. These anti-proliferation effects caused by IACS-010759 were fully rescued by NDI1 overexpression (**Figure 4B**), indicating high specificity of the inhibitor. Given IACS-010759's specific action on respiratory chain complex I, we pursued an additional method to inhibit OXPHOS in SCNC cell lines. We utilized IMT1B, a recently developed small molecule inhibitor of mitochondrial RNA polymerase (POLRMT), which blocks mitochondrial DNA transcription thereby downregulating all of the mitochondrially-encoded respiratory chain complexes[78]. Mirroring our findings with IACS-010759, IMT1B treatment more potently affected the POU2F3/ASCL2 subtype than the ASCL1 subtype (**Figure 4C**).

To extend our investigation of OXPHOS inhibition to other SCNC types, we examined the genetic dependencies of 104 lung cancer cell lines in the DepMap database. We first performed unsupervised principal component analysis (PCA) using the DepMap dependency scores. There was a distinct separation between SCLC and NSCLC samples (**Figure 4D**), indicating unique genetic dependencies between the two groups. Pathway enrichment analysis from the top and bottom 100 PC1 loading genes indicated that OXPHOS is a top enriched pathway in SCLC versus NSCLC cancer cell lines, implying that OXPHOS gene deletion has a stronger anti-proliferation effect in SCLC versus NSCLC (**Figure 4D**). Collectively, these findings indicate that OXPHOS, like PGC-1α, is necessary for the maintenance of SCNC cell lines, especially of the POU2F3/ASCL2 subtype.

<u>PGC-1α overexpression promotes OXPHOS in the prostate cancer ASCL1 subtype.</u>

As described above, PGC-1α inhibition reduced OXPHOS activity in SCNC cell lines. We

therefore asked whether PGC-1α overexpression is sufficient to promote OXPHOS, and whether this

metabolic shift would promote lineage plasticity. We first verified the PGC-1α overexpression construct

using western blot analysis in a panel of PARCB prostate cancer cell lines generated previously[2]. As

expected, PGC-1α overexpression increased both PGC-1α and OXPHOS protein levels (**Figure S4A**).

Next, PGC-1α was overexpressed in POU2F3/ASCL2 and ASCL1 PARCB tumor-derived cell lines, and

its effect on OXPHOS activity and neuroendocrine differentiation were measured. This analysis utilized

Seahorse respirometry, in vivo micro PET and computed tomography (microPET/CT) in vivo imaging,

and histology **(Figure 5A)**. PGC-1α overexpression upregulated OXPHOS activity in cells of the ASCL1

but not POU2F3/ASCL2 subtype (**Figure 5B**). This result is consistent with the ASCL1 subtype's selective

OXPHOS enhancement from yeast Complex I overexpression seen in Figure 4A, suggesting a relatively

fixed metabolic state in the POU2F3/ASCL2 subtype.

To check whether the increased OXPHOS caused by PGC-1α overexpression in cell lines would

translate to higher bioenergetics and SCN differentiation in tumors, ASCL1 or POU2F3/ASCL2 cell lines

with and without PGC-1α overexpression were xenografted into immunocompromised mice for tumor

initiation and subsequent microPET/CT imaging. PGC-1α overexpression promoted tumor growth only in

the ASCL1 subtype, but this effect did not reach statistical significance (**Figure 5C**). Although the effects

did not reach statistical significance, the increased tumor growth in the ASCL1 subtype was accompanied

by increased ^{18}F-FDG uptake (**Figure 5D**) and ^{18}F-BnTP[79] uptake in vivo (**Figure 5E**), indicating

heightened glucose uptake and mitochondrial content and/or activity, respectively.

We next checked whether tumors derived from ASCL2/POU2F3 or ASCL1 cell lines with PGC-

1α overexpression had increased SCN differentiation. We performed histological analysis from tumors

derived from both subtypes. There were no obvious histological changes in SCN differentiation upon

PGC-1α overexpression in either subtype (**Figure S4B**). Collectively, the data suggest that compared

with the ASCL1 subtype, the POU2F3/ASCL2 subtype exhibits a relatively fixed metabolic state, showing

a limited OXPHOS response to PGC-1α and NDI1 overexpression. Moreover, the data indicate that

despite the ASCL1 subtype's greater OXPHOS response to PGC-1α overexpression, PGC-1α alone is

not sufficient to trigger additional neuroendocrine differentiation in these terminally differentiated cell

lines.

<u>PGC-1α overexpression upregulates OXPHOS and drives SCN prostate cancer towards an ASCL1-</u>

<u>expressing lineage.</u>

In Figure 5 we showed that PGC-1α overexpression was not sufficient to induce lineage plasticity

of POU2F3/ASCL2 cells towards ASCL1, nor was it sufficient to induce further neuroendocrine

differentiation in terminally differentiated ASCL1 cells. We therefore asked whether PGC-1α

overexpression could promote SCN progression during PARCB transformation when the PARCB

oncogenes are actively restructuring the chromatin landscape to alter global gene expression. For this,

we conducted PARCB prostate transformation experiments with PGC-1α overexpression or control

constructs linked with BFP reporters, into the PARCB oncogene cocktail. (**Figure 6A**). PGC-1α

overexpression resulted in an approximate 100-fold increase in PGC-1α mRNA levels in PARCB prostate

organoids (**Figure S5A**) and a threefold higher tumor take rate compared with controls. (**Figure 6B**). The

majority of PGC-1α overexpressing tumors maintained high BFP expression months after transduction,

suggesting forward selection during transformation (**Figure S5B**). Consistently, PGC-1α protein levels

were higher in PGC-1α overexpressing tumors compared with control (**Figure S5C**). These data indicate

that PGC-1α overexpression promotes PARCB-induced SCN prostate tumor formation.

To better understand how PGC-1α overexpression promotes PARCB transformation, we

performed bulk RNA sequencing on PARCB tumors with PGC-1α overexpression and control. GSEA

revealed that PGC-1α overexpression in PARCB tumors upregulated OXPHOS gene expression (**Figure**

6C). Next, a detailed GSEA squared analysis was performed, ranking OXPHOS-related gene sets by

NES scores across multiple gene set families comprised over 10,000 gene sets (**Figure 6D**). This

analysis showed that OXPHOS gene sets were highly and exclusively enriched in PARCB tumors with

PGC-1α overexpression compared with control (**Figure 6D**). Thus, PGC-1α overexpression robustly

increases OXPHOS gene expression. Additionally, we explored adhesion-related pathways, known to be

broadly downregulated as cancers transition to a more SCN phenotype[1]. We observed a downregulation

of adhesion pathways in PARCB tumors that overexpressed PGC-1α, relative to the control group

(**Figure 6D**). These finding suggests that PGC-1α overexpression may promote SCN differentiation by

upregulating OXPHOS.

To quantify the effect of PGC-1α overexpression on SCN differentiation, we first categorized

tumors into PGC-1α-High and PGC-1α-Low groups, based on PGC-1α mRNA levels achieved by

overexpression. PGC-1α-high samples exhibited a higher SCN score (defined above, in the methods

section, and in reference[1]) compared with PGC-1α-low (**Figure 6E**). We also calculated SCN scores for

all 55 samples from our recently published PARCB time course study[13]. Notably, PGC-1α-high samples

not only displayed increased SCN differentiation in comparison to the PGC-1α-low samples from this

study, but also exhibited higher SCN scores than all samples from the temporal study (**Figure 6E**). To

determine whether these transcriptomic changes were mirrored at the protein level, we performed

immunohistochemistry in PARCB tumors sections with PGC-1α overexpression or control. Consistent

with the transcriptomic results in Figures 6C-6E, increased mitochondrial content (TOMM20) and

neuroendocrine (NCAM1) expression were observed in PGC-1α-High tumor sections compared with

PGC-1α-Low (**Figure 6F**). These results indicate that high levels of PGC-1α overexpression upregulate

OXPHOS expression and promote SCN differentiation.

Building on the established relationship between PGC-1α and ASCL1 described above, we

investigated if PGC-1α overexpression could promote lineage plasticity towards the ASCL1 subtype. By

conducting a gene expression analysis on PARCB tumors categorized by high versus low PGC-1α

expression and analyzing signature genes of both ASCL1 and POU2F3/ASCL2 subtypes, we detected a

distinct expression pattern. Notably, PGC-1α-high samples predominantly expressed genes associated

with the ASCL1 subtype, whereas PGC-1α-low samples exhibited an increased expression of

POU2F3/ASCL2 subtype genes (**Figure 6G**). This pattern underscores PGC-1α's potential influence in

steering lineage specificity towards ASCL1.

To determine if these expression patterns are observable in a broader clinical context, our

datasets from PARCB tumors with PGC-1α overexpression were projected onto datasets from SCLC

samples in the CCLE and from the clinical study by George et al. 2015[68] (**Figure 6H**). We also included

the ASCL1 and POU2F3/ASCL2 PARCB samples from our recently published study[13]. PGC-1α-high

samples clustered well with SCLC-ASCL1 and PARCB-ASCL1 tumors (HC6), whereas PGC-1α-low

samples clustered better with SCLC-POU2F3 and PARCB-POU2F3/ASCL2 tumors (HC5). Collectively,

these data suggest that PGC-1α promotes SCNC progression towards an ASCL1-expressing subtype

with increased OXPHOS capacity.

<u>ASCL1 overexpression upregulates PGC-1α expression</u>

Considering the shared molecular alterations in cells of both ASCL1 and POU2F3/ASCL2

subtypes, we aimed to identify the transcription factor specifically driving PGC-1α expression in the

ASCL1 lineage. Given ASCL1's role as a pioneer transcriptional activator, we focused on whether ASCL1

itself can influence PGC-1α expression. To this end, we analyzed data from our prior study where ASCL1

was overexpressed in two PARCB POU2F3/ASCL2 tumor-derived cell lines, which do not express PGC-

1α[13] (**Figure 7A**). ASCL1 overexpression switched on the expression of PGC-1α in both cell lines (**Figure**

7A). These results indicate that ASCL1 itself can regulate PGC-1α expression.

To validate this regulatory role of ASCL1 in PGC-1α expression, we investigated a newly

developed in vitro model for SCN prostate cancer differentiation focusing on the androgen-insensitive

C4-2B cell line[80]. This model induces SCN differentiation in C4-2B cells by incorporating a specific set of

SCN oncogenes and transcription factors, namely PRNBSAN (dominant-negative T<u>P</u>53, sh<u>R</u>B1, MYC<u>N</u>,

<u>B</u>CL2, <u>S</u>RRM4 combined with <u>A</u>SCL1, or <u>N</u>EUROD1) (**Figure 7B**). Consistent with the observations in

the PARCB models, we observed a tight expression correlation between PGC-1α and ASCL1 in this

model (**Figure 7C**). Moreover, ASCL1 overexpression (PRNBSA) elevated PGC-1α levels, which

correlated with enhanced SCN differentiation (**Figure 7D**). These findings establish ASCL1 as a positive

regulator of PGC-1α expression and reinforce the functional connection between PGC-1α, ASCL1, and

neuroendocrine differentiation.

To better understand how ASCL1 enhances PGC-1α expression, we explored its direct interaction

with gene promoters of PGC-1α. We analyzed ASCL1 ChIP-Seq datasets from SCN lung[81,82] and

prostate cancer cell lines[64,80], as well as in LuCaP prostate cancer patient-derived xenografts (PDXs)[12].

Our analysis indicated variable binding of ASCL1 to PGC-1α DNA, with inconsistent effects across

different studies and samples. Specifically, ASCL1's binding to an alternative promoter of PGC-1α,

particularly at exon 1b[74] encoding transcript variant X2 (XM_005248132.1), was modest in SCN lung and

prostate cancer cell lines but absent in prostate cancer PDX models (**Figures 7E and S6**). In contrast,

prostate cancer PDX models showed ASCL1 with a stronger affinity for variant 1 (NM_001330751.2) of

PGC-1α, a pattern not observed in SCN lung and prostate cancer cell lines (**Figure S7**). Additionally,

ASCL1's interaction within the PGC-1α gene body was exclusive to SCN lung cancer cell lines and was

not present in SCN prostate cancer cell lines and PDX models (**Figure S8**). The variable binding of

ASCL1 to PGC-1α DNA across datasets and model systems precludes definitive conclusions about

ASCL1's consistent interaction with the PGC-1α gene.

DISCUSSION

<u>Metabolic heterogeneity and plasticity in SCNC subtypes</u>

Our study sheds light on the role of mitochondrial metabolism on lineage plasticity in SCNCs. Our

findings reveal metabolic heterogeneity between the ASCL1 and POU2F3/ASCL2 SCNC subtypes,

distinguished by their respective PGC-1α expression and OXPHOS capacities. Specifically, the ASCL1

subtype has higher PGC-1α expression and OXPHOS activity compared with the POU2F3/ASCL2

subtype. Additionally, the ASCL1 subtype has increased metabolic flexibility as evidenced by its heighted

OXPHOS response to overexpression of both PGC-1α and NDI1, the respiratory chain complex I from

Saccharomyces cerevisiae. Conversely, the POU2F3/ASCL2 subtype has a more fixed metabolic state,

showing no OXPHOS response to the same genetic perturbations. Moreover, using genetic PGC-1α

gain-of-function during PARCB-induced SCN prostate transformation, we discovered that PGC-1α

triggers a metabolic shift towards OXPHOS and promotes differentiation towards an ASCL1-expressing

SCN prostate cancer subtype.

<u>The role of PGC-1α and OXPHOS during androgen deprivation therapy</u>

Recent studies indicate increased reliance of prostate cancer cells on OXPHOS after androgen

deprivation therapy (ADT)[83,84]. Consistently, our analysis of a clinical dataset in which tumors were

sampled from prostate cancer patients before and after ADT using enzalutamide[70] indicated that post-

treatment tumors had increased PGC-1α expression. Furthermore, OXPHOS was a top enriched

pathway upon ADT. These observations suggest that ADT may induce a strong selection pressure on

prostate cancer cells to increase their reliance on OXPHOS, thereby facilitating progression to the SCN

state. Thus, targeting the PGC-1α-OXPHOS axis during and after ADT may have a powerful therapeutic

effect against SCN prostate cancer progression.

<u>Targeting the PGC-1α-OXPHOS axis in SCNCs</u>

Although both subtypes were sensitive to PGC-1α and OXPHOS inhibition, the bioenergetically

quieter POU2F3/ASCL2 subtype was more sensitive to both perturbations than the ASCL1 subtype. The

heightened sensitivity of the POU2F3/ASCL2 subtype may be attributable to two characteristics: 1) its

lower levels of PGC-1α and OXPHOS activity, which makes it easier to reduce their levels, and/or 2) its

reduced metabolic flexibility, making it unable to shift its metabolic state to tolerate the OXPHOS

inhibition. Our characterization of the subtype-specific metabolic vulnerabilities within SCNCs may inform

therapeutic strategies.

In light of the intimate relationship between mitochondrial metabolism and cancer, OXPHOS

inhibitors are being actively explored as potential cancer treatments[47–49]. IACS-010759, a potent and

selective respiratory chain complex I inhibitor recently explored in clinical trials[47,85–87], can potentially be

repurposed to target SCNCs. Despite these initial trials being halted due to peripheral neurotoxicity and

lactic acidosis[88] (on target, off tumor toxicities), SCNCs of the POU2F3/ASCL2 subtype may demonstrate

a broader therapeutic window for this drug because of their increased reliance on OXPHOS. Notably,

IACS-010759 showed a partial response and alleviation of cancer-related pain in a patient with castration-

resistant prostate cancer[85,89]. However, the neuroendocrine differentiation status of the patient's cancer

is unknown.Targeting PGC-1α could be another approach to controlling SCNC progression. Although

direct inhibitors of PGC-1α are not currently available, there are several small-molecule inhibitors that

can regulate PGC-1α related pathways[73]. Most of these small molecules have been designed to activate

its expression. However, recent studies have also identified small molecules that can inhibit PGC-1α.

One such molecule is SR-18292[75], which increased PGC-1α lysine acetylation in hepatocytes by blocking

its interaction with the histone acetyltransferase KAT2A (GCN5), reducing genes involved in

gluconeogenesis[90,91]. In our study, PGC-1α inhibition with SR-18292 reduced the proliferation of PARCB-

tumor derived cell lines, with a more pronounced effect in the POU2F3/ASCL2 subtype. While this

inhibitor was reported to diminish OXPHOS activity[92], its PGC-1α-related roles beyond OXPHOS in

SCNCs warrants further investigation. Future research should also investigate the metabolic

vulnerabilities in the NEUROD1 and YAP1 subtypes, which were not addressed in our study.

<u>ASCL1's upstream regulation of PGC-1a initiates a potential positive feedback loop</u>

Our investigation into the ASCL1-PGC-1α interaction encompassed comprehensive

bioinformatics analyses of thousands of patient tumors, human cancer cell lines, and multiple clinical

SCNC datasets, along with functional experiments in SCNC models PARCB and PRNBSAN. These

efforts demonstrated a strong correlation between PGC-1α and increased ASCL1 expression.

Exogenously elevating ASCL1 levels enhanced PGC-1α expression, indicating that ASCL1 may be an

upstream activator of PGC-1α. Moreover, the PGC-1α overexpression experiments depicted in Figure 6

demonstrate that enhancing PGC-1α during PARCB transformation promotes lineage plasticity towards

the ASCL1 subtype. Together, these observations point to a potential positive feedback mechanism

where ASCL1 elevates PGC-1α levels, which in turn, further increases ASCL1 expression, thereby

intensifying PGC-1α's effect and encouraging lineage plasticity towards the ASCL1 subtype.

While analysis of existing ASCL1 ChIP-Seq datasets revealed some evidence of ASCL1 binding

to PGC-1α's promoters and gene body, hinting at a direct regulatory mechanism, inconsistencies across

datasets—likely due to differences in experimental sample types and the ASCL1 antibodies used—

render the direct binding role of ASCL1 to PGC-1α inconclusive. Thus further research is needed to

elucidate the precise interaction between PGC-1α and ASCL1, including the exploration of indirect

pathways by which ASCL1 may modulate PGC-1α levels. Future research should also investigate

whether PGC-1α can directly bind to ASCL1 to co-activate it. Considering the significant influence of the

tumor microenvironment on cancer progression[93], future studies should also investigate how external

microenvironmental factors may initiate or influence the genetic interaction between PGC-1α and ASCL1.

<u>Concluding remarks</u>

We identify PGC-1α as a driver of SCN prostate cancer, promoting lineage plasticity towards an

ASCL1-expressing subtype. Moreover, our findings reveal that the POU2F3/ASCL2 subtype

demonstrates an increased sensitivity to PGC-1α and OXPHOS inhibition, attributable to its distinct

metabolic profile. Specifically, it has relatively low levels of PGC-1α and OXPHOS, coupled with a

relatively fixed metabolic state compared to the ASCL1 subtype. These characteristics likely underpin

the POU2F3 subtype's vulnerability to inhibition of PGC-1α and OXPHOS. Collectively, these observation

suggests the need for tailored treatment strategies that account for each tumor subtype's unique

metabolic makeup. As research continues to unravel the intricate relationship between metabolic

reprogramming and SCNC progression, our findings should aid in developing more effective therapies

for these notoriously resistant cancers.

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507   C.C., J.F., T.H., W.T., K.S., F.N.E., L.W.; Investigation: G.V., D.C., F.N.E., G.A.B.; Resources: C.C.,

508   J.W.P., S.M.; Writing: Original Draft Preparation: G.V.; Writing: G.V., E.A., O.N.W.; Visualization: G.V.;

509   Supervision: S.M., T.G., O.S., O.N.W.

511   DECLARATION OF INTERESTS

O.N.W. currently has consulting, equity, and/or board relationships with Trethera Corporation, Kronos

Biosciences, Sofie Biosciences, Breakthrough Properties, Vida Ventures, Nammi Therapeutics, Two

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519   MAIN FIGURE LEGENDS

Figure 1. Elevated PGC-1α in clinical SCNC correlates with increased ASCL1 expression and neuroendocrine differentiation.

A. Gene expression analysis across all human cancer cell lines from the Cancer Cell Line Encyclopedia (CCLE). Left panel: co-expression analysis between PGC-1α and ASCL1, highlighting samples with high expression levels of both genes (boxed region). Right panel: pie charts illustrating the proportion of cancer types exhibiting elevated co-expression of PGC-1α and ASCL1, in contrast to the rest of the samples. See also Figure S1A.

B. Related to Figure 1A: Transcriptomic examination of small cell neuroendocrine (SCN) differentiation in CCLE human cancer cell lines. SCN scores (defined previously[3] and detailed in the Methods) are calculated for cells showing heightened PGC-1α and ASCL1 expression versus the rest of the cells.

C. Related to Figure S1C: A transcriptomic analysis of SCN differentiation in all the patient tumors from the TCGA database shown in Figure S1C. SCN scores are calculated from the boxed tumor samples with elevated PGC-1α and ASCL1 expression compared with the rest of the samples.

D. Gene expression analysis in multiple clinical SCNC datasets[67,68,94–97]. Left panel: co-expression analysis of PGC-1α and ASCL1. Right panel: SCN scores of the boxed samples with elevated PGC-1α and ASCL1 expression compared with the rest of the samples.

E. PGC-1α expression levels in multiple SCNC datasets. SCLC subtypes are denoted as follows: P, POU2F3; A, ASCL1; N, NEUROD1; Y, YAP1. The datasets used are indicated.

F. Transcriptomic analyses in clinical prostate cancer tumors before and after androgen deprivation therapy (ADT) with enzalutamide. Left panel: a schematic overview. Middle panel: Comparison of PGC-1α expression levels pre- and post-ADT. Right panel: Co-expression analysis of PGC-1α and ASCL1 in (combined pre- and post-treatment analysis). See also Figure 1G.

G. Gene set enrichment analysis (GSEA) of differentially expressed genes in pre- versus post ADT-treated tumors. See also Figure 1F.

Data for Figures 1B-1F are expressed as mean ± SEM, with significance denoted as **** (p≤0.0001), ** (p≤0.01), and * (p≤0.05). The green lines represent the best-fit linear regression model, with the

indicated R^2 and p-values. All Log2 values have been upper quartile normalized with a pseudocount

of 1 (Log2 UQN+1). For statistical tests used, see Material and Methods section.

Related data can be found in Figure S1. Abbreviations: SCLC, small cell lung cancer; NEPC,

neuroendocrine prostate cancer; CRPC, castration resistant prostate cancer; LUAD, lung

adenocarcinoma.

Figure 2. Enhanced PGC-1α expression and OXPHOS activity in SCN prostate cancer within the ASCL1

tumor subtype.

A. Schematic illustrating PARCB-induced SCN prostate transformation, highlighting the bifurcation

of end stage tumors into the POU2F3/ASCL2 and ASCL1 lineages.

B. Co-expression analysis of PGC-1α and ASCL1 during PARCB prostate transformation. Note that

tumors with the highest expression levels of both genes are exclusively found in the ASCL1

subtype.

C. Analysis of PGC-1α expression levels during PARCB transformation in 5 out of 10 patient series

showcasing increased PGC-1α expression over time.

D. Comparative expression levels of PGC-1α in POU2F3/ASCL2 versus ASCL1 PARCB tumor

subtypes indicating subtype-specific expression patterns.

E. Hypergeometric Optimization of Motif EnRichment (HOMER) analysis across PARCB tumors

from both POU2F3/ASCL2 and ASCL1 subtypes. PGC-1α interacting transcription factors were

identified from the STRING database[98].

F. GSEA in the ASCL1 tumor subtype versus the rest of the PARCB time course samples. Gene

Ontology Biological Process (GOBP) gene sets were used. The pie chart indicates the proportion

of enriched gene sets related to mitochondrial OXPHOS.

G. Seahorse respirometry in PARCB tumor-derived cell lines from both the POU2F3/ASCL2 and

ASCL1 subtypes. Inhibitors used: Oligo, Oligomycin; FCCP, Carbonyl cyanide-p-

trifluoromethoxy-phenylhydrazone; Rot/AA, rotenone / antimycin A.

H. Expression of the mitochondrial pyruvate carrier in ASCL1 and POU2F3/ASCL2 PARCB tumor subtypes.

All data, except in Figure 2G, utilizes data extracted from our recently published Chen et al. 2023 dataset[13]. The black line in Figure 2B represents the best-fit linear regression model, with the indicated R^2 and p-values. Data in Figures 2D, 2G, and 2H are presented as mean ± SEM, with significance levels marked as follows: **** (p≤0.0001), *** (p≤0.001), ** (p≤0.01), and * (p≤0.05). All Log2 values are Log2 UQN+1. For statistical tests used, see Material and Methods section.

Related data can be found in Figure S2.

Figure 3. PGC-1α inhibition blunts OXPHOS, reduces the growth of SCNC cell lines, and blocks SCN prostate tumor formation.

A. Schematic illustrating PARCB prostate transformation with PGC-1α knockdown.

B. PGC-1α mRNA levels using RT-qPCR in PARCB-transduced prostate organoids.

C. Cell proliferation analysis in ASCL1 tumor-derived cell lines from the PARCB model, comparing PGC-1α knockdown (KD) cells to control. The blue fluorescence in the micrographs is derived from the shPGC-1α and shControl constructs, which have co-linked expression of a blue florescence protein (EBFP2).

D. Cell proliferation analysis in POU2F3/ASCL2 tumor-derived cell lines from the PARCB model with PGC-1α KD versus control.

E. Cell proliferation analysis of a patient-derived SCN prostate cancer cell line (NCI-H660) with PGC-1α KD compared with control.

F. PGC-1α inhibition (RNAi) effects on cell proliferation, represented by a dependency scores from the DepMap database. a score of zero signifies no proliferation impact, negative values indicate decreased proliferation, and a score of negative one corresponds to the median effect across all pan-essential genes.

G. Seahorse respirometry in PARCB cell lines derived from the POU2F3/ASCL2 and ASCL1 tumor subtypes. Oligo, Oligomycin; FCCP, Carbonyl cyanide-p-trifluoromethoxy-phenylhydrazone; Rot/AA, rotenone / antimycin A.

Data in parts D, G, and H are presented as mean ± SEM, with significance levels marked as follows: *** (p≤0.001), ** (p≤0.01), and * (p≤0.05). For statistical tests used, see Material and Methods section.

Related data can be found in Figure S3.

Figure 4. OXPHOS inhibition blunts SCN prostate and lung cancer cell line proliferation.

A. Seahorse respirometry in cell lines derived from the PARCB POU2F3/ASCL2 and -ASCL1 tumor subtypes with the indicated conditions. Oligo, Oligomycin; FCCP, Carbonyl cyanide-p-trifluoromethoxy-phenylhydrazone; Rot/AA, rotenone / antimycin A.

B. Cell proliferation analysis of cell lines derived from the POU2F3/ASCL2 and ASCL1 PARCB tumor subtypes with the indicated treatments.

C. Cell proliferation analysis of cell lines derived from the PARC-POU2F3/ASCL2 and -ASCL1 tumor subtypes treated with a mitochondrial DNA-directed RNA polymerase (POLRMT) inhibitor (IMT1B) to block OXPHOS.

D. Analysis of differentially dependent genes in NSCLC and SCLC cell lines. Left panel: unsupervised principal component analysis (PCA) on the genetic dependency data from all of the lung cancer cell lines in the DepMap dataset. Right panel: normalized enrichment scores of gene sets that separate PC1 low (SCLC) and PC1 high (NSCLC). The top 100 genes from the PC1 loading scores were used as input.

Data in Figure 4B are represented as mean ± SEM. with statistical significance denoted as *** (p≤0.001) and ** (p≤0.01). For statistical tests used, see Material and Methods section.

Figure 5. PGC-1α overexpression promotes OXPHOS in the SCN prostate cancer ASCL1 subtype.

A. Left panel: overview of experimental strategy. Right panel: Details on the Positron Emission Tomography (PET) probes utilized and their general mechanisms of action.

B. Seahorse respirometry in POU2F3/ASCL2 and ASCL1 PARCB tumor-derived cell lines. Oligo, Oligomycin; FCCP, Carbonyl cyanide-p-trifluoromethoxy-phenylhydrazone; Rot/AA, rotenone / antimycin A.

C. Caliper measurements of tumors initiated by subcutaneous injection of POU2F3/ASCL2 and ASCL1 PARCB cell lines with PGC-1α overexpression versus control.

D. Left panel: overlay of in vivo micro PET and computed tomography (microPET/CT) scanning of a mouse with a subcutaneous ASCL1 PARCB tumor imaged with ^{18}F-FDG indicting glucose uptake. Right panel: quantification of ^{18}F-FDG uptake.

E. Left panel: microPET/CT of a mouse with a subcutaneous ASCL1 tumor imaged with ^{18}F-BnTP. Right panel: quantification of ^{18}F-BnTP uptake indicating mitochondrial content. The inset has been contrast enhanced to show the relatively low uptake of this probe in subcutaneous tumors, as reported previously[99].

Data in Figure 5B are presented as mean ± SEM, with *** indicating a p-value ≤0.001. For statistical tests used, see Material and Methods section. The absence of asterisks indicates that statistical significance of p≤0.05 was not reached.

Related data can be found in Figure S4.

Figure 6. PGC-1α overexpression upregulates OXPHOS and drives SCN prostate cancer towards an ASCL1-expressing lineage.

A. Schematic illustrating the experimental setup for assessing the effects of PGC-1α overexpression versus a control vector on PARCB-induced prostate cancer transformation.

B. Comparison of the tumor establishment rate ("tumor take rate") between PARCB transformation using PGC-1α overexpression compared with control. PARCB transformations were performed

using three separate patient donors, resulting in a total of 45 xenografts being implanted in 23

mice.

C. GSEA in PARCB tumors with PGC-1α overexpression versus control.

D. GSEA squared analysis depicting the distribution of normalized enrichment scores (NES) for

thousands of gene sets across multiple gene set families in samples with PGC-1α overexpression

versus control. See Materials and Methods section for details.

E. A transcriptomic analysis of SCN differentiation comparing SCN scores in PGC-1-High versus

PGC-1α-Low PARCB tumors. SCN scores calculated from datasets derived from Chen et al

2023[13] are also shown for comparison.

F. Immunohistochemistry in histological sections derived from PARCB tumors with high and low

levels of PGC-1α.

G. A heatmap displaying normalized gene expression levels for signature genes related to

POU2F3/ASCL2 and ASCL1 tumor subtypes in PGC-1α-High versus PGC-1α-Low tumors.

H. Principal Component Analysis (PCA) of PARCB samples, distinguishing between PGC-1α-High

and PGC-1α-Low PARCB tumors from this study, overlaid on PARCB tumors from our prior time

course study[13] and SCLC cell lines from the CCLE and George et al. 2015 clinical study[68].

Data in Figure 5E are presented as mean ± SEM, with statistical significance indicated by ****

(p≤0.0001) and *** (p≤0.001). For statistical tests used, see Material and Methods section.

Related data be can found in Figure S5.

Figure 7. ASCL1 overexpression upregulates PGC-1α expression

A. Expression levels of ASCL1 (left panel) and PGC-1α (right panel) after acute overexpression of

ASCL1 in cell lines derived from the PARCB POU2F3/ASCL2 tumor subtype. Data are mined

from Chen et al 2023[13]. Log2 values are Log2 UQN+1.

B. Schematic illustrating transformation of C42B cells to SCN prostate cancer using the PRNBSAN oncogenes and transcription factors (dominant-negative TP53, shRB1, MYCN, BCL2, SRRM4, ASCL1, and NEUROD1).

C. Co-expression analysis of PGC-1α and ASCL1 in C4-2B cells from the PRNBSAN transformation system. Log2 values are Log2 FPKM+1.

D. Expression analysis of ASCL1 (top panel) and PGC-1α (bottom panel) from C4-2B cells transduced with PRNBSAN. Log2 values are Log2 FPKM+1. The arrow indicates increased SCN differentiation as observed Li et at. 2024[80].

E. ASCL1 ChIP Seq analysis in SCN prostate cancer and lung cancer cell lines from Li et al. 2024 and Augustyn et al. 2014. This gene locus represents Exon 1b, encoding transcript variant X2 (XM_005248132.1).

The data for Figure 7A and 7D are presented as mean ± SEM, with statistical significance denoted by ** (p≤0.01). For statistical tests used, see Material and Methods section.

Related data can be found in Figures S6-8.

MATERIALS AND METHODS

PARCB + PGC-1α transformation

Donor prostate tissues were obtained in a de-identified manner and were therefore exempt from Institutional Review Board (IRB) approval. The PARCB transformation assay was performed as described previously[6] with modifications to the viral constructs to include PGC-1α gain- and loss-of-function analyses. Briefly, donor prostate tissues were digested overnight and isolated cells were stained to identify the basal cells. FACS sorted basal cells were combined with PARCB oncogene lentiviruses at an MOI of 50 in Matrigel (Cat# 356234, Corning). The mixtures of basal cells, viral supernatant, and Matrigel were plated in 48-well plates as hanging drop cultures until Matrigel solidified into domes. 20,000 basal cells were used per Matrigel dome, in a final volume of 20-30 μl per well. After Matrigel solidification,

708 organoids were cultured in prostate organoid media[78] at 37°C and 5% CO2 for 10-14 days. Transduced

709 organoids were harvested by dissociation of Matrigel with 1mg/mL Dispase (Cat# 17105041, Thermo

710 Fisher Scientific) and washed three times with PBS to remove Dispase. Washed organoids were re-

711 suspended in 10 µl of normal Matrigel and 10 µl Matrigel with high growth factors (Cat# 354248, Corning).

712 The organoid-Matrigel mixtures were implanted subcutaneously in immunodeficient NOD.Cg-Prkdcscid

713 Il2rgtm1Wjl/SzJ (NSG) mice[79] to initiate tumor formation. Tumors were extracted before ulceration or

714 reaching around 1 cm in diameter, whichever came first. NSG mice were obtained from the Jackson

715 Laboratories and housed and bred under the care of the Division of Laboratory Animal Medicine at the

716 University of California, Los Angeles (UCLA). All animal handling and subcutaneous injections were

717 performed following the protocols approved by UCLA's Animal Research Committee.

719 ***Cell lines and culture media***

720 The SCN prostate cancer line NCI-H660 (Cat# CRL-5813) was purchased from American Type Culture

721 Collection (ATCC). The PARCB-P3-TP5, PARCB-P2-TP6, and PARCB-P7-TP6 cell lines[13] and PARCB-

722 1, PARCB-11[2] cell lines were generated previously. All cells were maintained in stem cell culture media

723 (SCM): Advanced DMEM/F12 (Gibco CAT# 12634028), Glutamax (Gibco, CAT# 35050061), Pen/Strep,

724 B27 (Gibco CAT# 17504044), 10ng/ml human EGF (Peprotech CAT# 100-47, and 10ng/ml human FGF-

725 basic (Peprotech CAT# 100-18B). All cell lines were routinely tested for Mycoplasma using a MycoAlert™

726 PLUS Mycoplasma Detection Kit (Cat# LT07-703, Lonza).

728 ***Lentiviral vectors and high-titer lentivirus production***

729 The following three vectors for PARCB transformation were described previously: mristoylated AKT1

730 (FU-myrAKT1-CGW), c-MYC and BCL2 (FU-cMYC-P2A-BCL2-CRW), dominant negative TP53 (R175H)

731 and shRNA targeting of RB1 (FU-shRB1-TP53DN-CYW)[6]. For PGC-1α overexpression, a fourth vector

732 was designed. First, an FUGW backbone was subcloned to replace the EGFP with EBFP2 using Gibson

733 assembly (referred to as FUBW). Next, PGC-1α cDNA from pcDNA4 myc PGC-1 alpha (Addgene

734 #10974) was cloned into the FUBW backbone driven by a ubiquitin promoter. An empty FUBW backbone

without PGC-1α cDNA was used as a control. For PGC-1α inhibition during PARCB transformation,

shRNA targeting PGC-1α was cloned into the myristoylated AKT1 vector (FU-myrAKT1-CGW),

downstream of the H1 promoter. The following PGC-1α targeting sequence was used

TATGACAGCTACGAGGAATAT. As a control, a sequence that targets no known mammalian genes was

used (CAACAAGATGAAGAGCACCAA). For PGC-1α inhibition in cultured cell lines, the same shRNA

sequences were cloned into a pLKO_005 backbone, which was subcloned to replace its puromycin

resistance gene along with its promoter with CMV-EBFP2. High titer lentiviruses were made using a

previously established method[162].

Transduction of cultured SCN cell lines

Cultured SCN cell lines, which grow in suspension as clusters, were mechanically dissociated using

gentle pipetting with a P1000 pipette. 600,000 live cells were seeded in non tissue culture treated 12-well

plates and transduced with high titer lentiviruses at an MOI of 2-5 in the presence of polybrene and ROCK

inhibitor. The plates were subsequently centrifuged at 1,000 g for 90 min at RT, followed by overnight

incubation. The following morning, 1 ml fresh SCM was added to each well and the cells were gently

mixed with a P1000 to dislodge any adhered cells. 48-72 hours after transduction, BFP positive cells

were sorted to enrich for transduced cells. After a 24-hour recovery period, cells were used for

downstream analyses.

Inhibition of PGC-1α and OXPHOS

For pharmacological inhibition of PGC-1α (with SR-18292) and OXPHOS (with IACS-010759 and

IMT1B), 96-well plates were pre-filled with SCM media (described above) containing each of the inhibitors

or DMSO as a control. Cell growth was quantified using the Cell Titer-Glo Luminescent Cell Viability

Assay (Cat# G7570, Promega) as described below.

Cell proliferation assay

2,000 - 10,000 cells per cell line in 3-6 replicates were seeded into black, opaque 96-well plates with a

glass bottom. Cell content was measured on Days 1-6 using Cell Titer-Glo Luminescent Cell Viability

Assay (Cat# G7570, Promega). Luminescence was measured at an integration time of 0.5 second per

well. The number of cell doublings were calculated between the day of plating, and the termination of the

assay, indicated on each figure panel. Because CTG uses an ATP-based readout, and since the

mitochondrial inhibitors influence the amount of ATP in the cell, the internal GFP, driven by the AKT1

(FU-myrAKT1-CGW) vector was also quantified using microscopy and a plate reader. Consistent results

were obtained with both techniques.

RT-qPCR

Total RNA was isolated from cells using miRNeasy Mini Kit (Cat# 217004, Qiagen). cDNA was

synthesized from 2 ug of total RNA using the SuperScript IV First-Strand Synthesis System (Cat#

18091050, Thermo Fisher). RT-qPCR was performed using SYBR Green PCR Master Mix (Cat#

4309155, Thermo Fisher). Amplification was carried out using the StepOne Real-Time PCR System

(Cat# 4376357, Thermo Fisher) and analysis was performed using the StepOne Software v2.3. Relative

quantification was determined using the Delta-Delta Ct Method. The following primer pair was used to

amplify PGC-1α mRNA:

CCTGCTCGGAGCTTCTCAAA

CCCTTGGGGGTCATTTGGTGA

Tissue section, histology, and immunohistochemistry (IHC)

PARCB tumors were fixed by overnight nutation in 10% buffered formaldehyde (SF100-4) at 4℃ followed

by three washes in 70% ethanol. Hematoxylin and eosin (H&E) staining was performed by UCLA's

Translation Pathology Core Laboratory (TPCL) using standard protocols. TPCL is a CAP/CLIA certified

research facility in the UCLA Department of Pathology and Laboratory Medicine and a UCLA Jonsson

Comprehensive Cancer Center Shared Facility. For immunohistochemistry, formalin-fixed, paraffin-

embedded (FFPE) PARCB tumors were deparaffinized in xylene and rehydrated. Citrate buffer (pH=6.0)

was used for antigen retrieval. The sections were incubated in citrate buffer and heated in a pressure

cooker. 3% H2O2 in methanol was used to block endogenous peroxidase activity for 10 min at room

temperature. The sections were blocked then incubated with primary antibodies overnight at 4°C. Anti-mouse/rabbit secondary antibodies were used to detect proteins of interest and DAB EqV substrate was used to visualize the staining. All components were included in the ImmPRESS Kit (MP-7801-15 and MP-7802-15, Vector Laboratories). The slides were then dehydrated and mounted with Xylene-based drying medium (Cat# 22-050-262, Fisher Scientific).

Western blot

1 million viable cells were lysed on ice using RIPA lysis buffer (Cat#89900, Thermo Fisher). Protein concentrations were measured using the Pierce BCA Protein Assay Kit (Cat#: 23227, Thermo Scientific). Samples were electrophoresed on polyacrylamide gels (Cat# NW04120BOX, Thermo Fisher), transferred to PVDF membranes (Cat# IPVH00010, Millipore). Western blots were visualized using iBright CL1500 Imaging system (Cat#44114, Thermo Fisher).

Antibodies

The following antibodies were used: PGC-1α ms monoclonal 4C1.3 (Sigma, ST1202), TOMM20 ms monoclonal (Santa Cruz Biotechnology, sc-17764), NCAM1/CD56 (Abcam, ab133345), and OXPHOS cocktail ms monoclonal (Abcam, ab110411).

Bulk RNA sequencing and dataset collection

Tumors were dissociated into single cells, followed by cell sorting of quadruple colors (BFP, GFP, YFP, and RFP) by flow cytometry. Total RNA was extracted from the cell lysates using the Zymo Direct-zol RNA Miniprep Plus Kit (Cat. No: R2072). Quality check was performed on the Agilent 4200 Tapestation (Agilent Technology; cat. no. G2991BA). Libraries for RNA-Seq of PARCB with PGC-1α overexpression and control samples were prepared with KAPA Stranded mRNA-Seq Kit (Cat# KK8420, Roche). The workflow consists of mRNA enrichment and fragmentation. Sequencing was performed on Illumina Hiseq 3000 or NovaSeq 6000 for PE 2x150 run. Data quality check was done on Illumina SAV. Demultiplexing was performed with Illumina Bcl2fastq v2.19.1.403 software. Raw sequencing reads were processed

through the UCSC TOIL RNA Sequencing pipeline for quality control, adapter trimming, sequence alignment, and expression quantification. Briefly, sequence adapters were trimmed using CutAdapt v1.9, sequences were then aligned to human reference genome GRCh38 using STAR v2.4.2a and gene expression quantification was performed using RSEM v1.2.25 with transcript annotations from GENCODE v23[83].

The FASTQ files of the Park dataset[6], Beltran dataset[33], George dataset[32], Rajan dataset[124] (GSE48403), and Chen dataset were all processed through the TOIL pipeline with the same parameters to get RSEM expected counts. The TOIL-RSEM expected counts of TCGA pan cancer samples were obtained directly from UCSC Xena browser (https://xenabrowser.net/datapages) and RSEM read counts of pan-cancer cell lines from the Cancer Cell Line Encyclopedia (CCLE) were downloaded from DepMap Portal (DepMap Public 22Q1) (https://depmap.org/portal/download/all/). The RSEM counts of all combined datasets were upper quartile normalized with a pseuodocount of 1 and log2 transformed (referred to as log2 (UQN+1) counts) and filtered down to HUGO protein coding genes (http://www.genenames.org/) for the downstream analyses. SCLC subtypes[43] and CRPC subtypes[54] were previously defined.

Sequencing of high-grade serous ovarian carcinomas (HGSOC) was approved through UCLA Institutional Review Board (IRB) approved protocols (IRB #10-000727, IRB #20-001626). Tumor specimens were obtained from high-grade serous ovarian cancer patients who had given their informed consent. RNA was isolated from both solid tumors collected from primary and metastatic sites, and effusion samples such as ascites and pleural fluid. Dissociated or cryopreserved tumor fragments were used for isolation of RNA. These samples were collected at various disease time points: chemonaive, post adjuvant or neoadjuvant chemotherapy, and at disease recurrence. Presence of tumor cells was confirmed on histologic sections. RNA isolation, library preparation, and sequencing were conducted by the Technology Center for Genomics and Bioinformatics (TCGB) core facility at UCLA.

Differential gene expression analysis and hierarchical clustering

Differential expression analysis was performed on raw RSEM expected count data of protein-coding genes using the R package DESeq2[100].

Gene set enrichment analysis (GSEA) and GSEA-squared

Differential gene expression analysis was first performed on raw RSEM expected count data of protein-coding genes on the Rajan 2014[124] dataset between Pre-ADT and Post-ADT samples.

Using the fgsea R package (https://github.com/ctlab/fgsea), gene set enrichment analysis (GSEA) was then performed on the hallmark (H), canonical pathways (CP), and gene ontology (GO) gene sets from MSigDB[101]. Additional mitochondria related gene sets were also included from MitoCarta3.0. The ranked list of genes was generated using the signed log2 fold change and -log10 transformed p-values calculated by DESeq2[102]. GSEA results were then ranked by Normalized Enrichment Score (NES) to identify highly enriched gene sets. To investigate pathways broadly related to our highly enriched gene sets (e.g., oxidative phosphorylation and adhesion), GSEA-Squared analysis was performed. In short, gene sets were ranked by NES and marked for if they contained a key term from that category of terms in the pathway name. KS tests were then performed using ks.test.2 to assess the distribution of the category of terms[102]. The keys used were the following:

Oxidative Phosphorylation, OXIDATIVE PHOSPHORYLATION, ELECTRON TRANSPORT, MITOCHONDRIAL COMPLEX, NADH DEHYDROGENASE, MITOCHONDRIAL LARGE RIBOSOMAL; OXPHOS

Adhesion, ADHESION, ADHERENS

Differential gene expression analysis was also performed on raw RSEM expected count data of protein-coding genes on the Chen 2014[32] dataset between HC6/ Class II/ ASCL1+ tumors and the rest of the samples in the dataset. Similar methods were used to perform gene set enrichment analysis on GO BP 2021 gene sets from MSigDB, except genes were ranked by their adjusted p-value.

Principle component analyses

Unsupervised principal component analysis (PCA) was performed on log2 transformed upper quartile normalized RSEM expected count data. The prcomp function in R was run centered and unscaled. Data

870 was projected onto the PCA framework by multiplying the rotation matrix by the projected data's

871 expression matrix.

Small cell neuroendocrine (SCN) score

874 SCN score was calculated as previously described in Balanis et al[1]. Briefly, PC1 loadings were taken

875 from a pan-cancer PCA which followed non-small cell cancers along their transdifferentiation trajectory

876 towards an SCN phenotype. A higher SCN score indicates a more SCN-like phenotype, while a lower

877 SCN score indicates a more normal, non-SCN-like phenotype.

Motif analysis

ATAC sequencing data was obtained from Chen 2023 dataset[32]. The raw FASTQ files were processed

using the published ENCODE ATAC-Seq Pipeline (https://github.com/ENCODE-DCC/atacseq-pipeline).

The reads were trimmed and aligned to hg38 using bowtie2. Picard was used to de-duplicate reads,

which were then filtered for high-quality paired reads using SAMtools. All peak calling was performed

using MACS3. The optimal irreproducible discovery rate (IDR) thresholded peak output was used for all

downstream analyses, with a threshold P value of 0.05. Other ENCODE3 parameters were enforced with

the flag-encode3. Reads that mapped to mitochondrial genes or blacklisted regions, as defined by the

ENCODE pipeline, were removed. The peak files were merged using bedtools merge to create a

consensus set of peaks across all samples, and the number of reads in each peak was determined using

bedtools multicov[103]. A variance stabilizing transformation was performed on peak counts using

DESeq2[100] and batch effects were removed using removeBatchEffect from limma[104]. DESeq2 was then

used to variance stabilize transform read counts and determine hyper- and hypo-accessible peaks across

HC5 and HC6 PARCB time course samples, using default parameters and without independent filtering

or Cook's cutoff. Peaks were called as hyper or hypo-accessible using abs(log2 fold change)>2 and

adjusted p<0.05. Motif analysis was then run separately on hyper- or hypo-accessible peaks in the HC5

versus. HC6 comparison using HOMER[105] with the flags -size 200 and -mask. Motifs were then ranked

by their p-value for hyper- or hypo-accessible peak sets. Motifs specific to hyper or hypo accessible

peaks were obtained by taking the rank difference of the motifs in the two lists.

Single-cell RNA sequencing

Single-cell expression levels of ASCL1, PGC-1α, ASCL2, and POU2F3 in PARCB time course tumors

were extracted from our recently published study[13]. Gene expression was visualized using Uniform

Manifold Approximation and Projection (UMAP) analysis as described previously[13]. The downstream

quality control, as well as batch integration and correction of PARCB single cell RNA-seq data were

performed as described previously[13]. Briefly, visualization of PARCB single cell RNA-seq data was

performed using the Seurat (5.0.3) R package[106]. The top 30 principal components were used to perform

UMAP analysis. Cell clustering was performed with FindNeighbors function with top 30 principal

components and FindClusters function with resolution of 0.5.

Seahorse respirometry

Respirometry experiments were performed on a Seahorse XF96 Extracellular Flux Analyzer (Agilent

Technologies). PARCB tumor-derived cell lines were process and counted as described, washed into

Seahorse Assay medium (Seahorse XF Base Medium supplemented with 2 mM L-glutamine, 1 mM

pyruvate and 10 mM glucose) and immediately seeded into an XF96 microplate, pre-coated with PDL.

Cells were plated at a density of 40,000 cells per well in a final volume of 175 µl. Prior to the start of the

assay, the XF96 plate was placed in a 37 °C incubator without CO2 for 30 min. During the assay, the

following compounds were injected: the mitochondrial ATP synthase inhibitor oligomycin (final

concentration 2 µM); the mitochondrial uncoupler FCCP (final concentration 1 µM); and the complex I

and III inhibitors rotenone (final concentration 2 µM); and the complex III inhibitor antimycin A (final

concentration 2 µM). At the conclusion of the assay, the cells were fixed with 4% paraformaldehyde,

stained with Hoechst, and cell number per well was determine based on nuclei number using an Operetta

High-Content Imaging System (PerkinElmer). OCRs were normalized to cell number per well.

microPET/CT imaging of tumor metabolism

Tumor-bearing mice were injected with 60 μCi of [^{18}F]-FDG (PETNET Solutions) or [^{18}F]-BnTP (prepared as previously described[107] through tail vein intravenous injections. Following a 60-minute unconscious uptake of the imaging tracer, mice were anesthetized with 2% vaporized isoflurane, and microPET (energy window 350-650 keV, 10-min static scan) and microCT (voltage 80 kVp, current 150 μA, 720 projections, 200μm resolution, scan time 1 min) images were acquired on a GNEXT PET/CT scanner (Sofie Biosciences, Dulles, VA). The microPET images were reconstructed using a 3D-Ordered Subset Expectation Maximization (OSEM) algorithm (24 subsets and 3 iterations), with random, attenuation, and decay correction. The microCT images were reconstructed using a Modified Feldkamp Algorithm. Amide software was used to analyze co-registered microPET/CT images. Representative maximum-intensity-projection (MIP) images are shown.

Chromatin immunoprocepticiation sequencing (ChIP-Seq)

To analyze the regulatory impact of ASCL1 on PGC-1α, we utilized Chromatin Immunoprecipitation Sequencing (ChIP-Seq) data from several studies, including Augustyn et al., 2014 (GSE61197), Borromeo et al., 2016 (GSE69398), Cejas et al., 2021 (GSE156290), and Nouruzi et al., 2022 (GSE183198), which were downloaded directly from the Gene Expression Omnibus (GEO). We converted data from bedGraph and wig formats to bigWig format using the UCSC bedGraphToBigWig and wigToBigWig tools to standardize data representation. To align all datasets to a consistent reference genome, we lifted data initially mapped to hg19 over to hg38 using the UCSC liftOver tool. For the Li et al., 2024 ChIP-Seq dataset, we merged bigWig files from replicates at each timepoint using the UCSC bigWigMerge tool, aiming to consolidate data for comprehensive analysis. Visualization of the processed datasets was performed with the Integrative Genomics Viewer (IGV 2.17.1), ensuring uniform background noise levels across samples to facilitate accurate comparison.

SUPPLEMENTAL FIGURE LEGENDS

Figure S1. Related to Figure 1.

A. Related to Figure 1A. Gene expression analysis of PGC-1α versus the SCNC lineage markers POU2F3, NEUROD1, and YAP1 in all the human cancer cell lines from the cancer cell line encyclopedia (CCLE).

B. Related to Figure 1A. PGC-1α expression levels in non-small cell lung cancer (NSCLC), small cell lung cancer (SCLC), and neuroblastoma (NB) cell lines from the CCLE.

C. Co-expression analysis of PGC-1α and ASCL1 in all tumor samples from The Cancer Genome Atlas (TCGA).

D. Co-expression analysis of PGC-1α and ASCL1 in a cohort of patients with high-grade serous ovarian carcinomas (HGSOC).

The data for Figure S1B are presented as mean ± SEM, with statistical significance denoted by *** (p≤0.001). The green lines represent the best-fit linear regression model, with the indicated R^2 and p-values. All Log2 values are Log2 UQN+1. For statistical tests used, see Material and Methods section

Figure S2. Related to Figure 2.

Expression levels of PGC-1α vs ASCL1, POU2F3, ASCL2 expression in single cells from the PARCB time course tumors from Chen et al. 2023[13].

Figure S3. Related to Figure 3

Cell proliferation analysis of PARCB tumor-derived cell lines treated with SR-18292, a pharmacological inhibitor of PGC-1α.

Figure S4. Related to Figure 5

A. Western blot analysis of PGC-1α overexpression effects on the expression levels of all five respiratory chain complexes in a panel of 4 PARCB tumor-derived cell lines. The PARCB cell lines were generated previously[2]

B. H&E staining in tumor sections from POU2F3/ASCL2 and ASCL1 PARCB tumors with PGC-1α

overexpression and control. These tumors were generated from terminally differentiated PARCB

cell lines re-injected into mice for tumor growth, as described in Figure 5. Note the increased

vasculature of POU2F3/ASCL2 tumors upon PGC-1α overexpression. Scale bars are 60 µm.

Figure S5. Related to Figure 6

A. PGC-1α mRNA levels using RT-qPCR in PARCB organoids with PGC-1α overexpression versus

control. Organoids were harvested just before xenografting.

B. Flow cytometry and fluorescence microscopy analysis of PARCB tumors with PGC-1α

overexpression and control. The PGC-1α overexpression and control constructs include a blue

fluorescence protein encoded by EBFP2. See Materials and Methods section for more details.

C. Western blot analysis of PGC-1α protein levels in PARCB tumors with PGC-1α overexpression

versus control. HEK 293T cells overexpressing PGC-1α were included as an additional control.

Figure S6. Related to Figure 7

ASCL1 ChiP-Seq analyses showing the alternative promoter of PGC-1α corresponding to variant

X2 (XM_005248132.1) encoded by exon1b. The following datasets were used: SCN lung cancer

cell lines[81,82], SCN prostate cancer cell lines[64,80], and LuCaP prostate cancer patient-derived

xenografts (PDXs)[12].

Figure S7. Related to Figure 7

ASCL1 ChiP-Seq analyses highlighting variant 1 of PGC-1α (NM_001330751.2) (red box). The

following datasets were used: SCN lung cancer cell lines[81,82], SCN prostate cancer cell lines[64,80],

and LuCaP prostate cancer patient-derived xenografts (PDXs)[12].

Figure S8. Related to Figure 7

ASCL1 ChiP-Seq analyses indicating a region within the PGC-1α gene body. The following datasets were

used: SCN lung cancer cell lines81,82, SCN prostate cancer cell lines64,80, and LuCaP prostate cancer

patient-derived xenografts (PDXs)12.

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1231

Figure 1

Figure 2

Figure 3

Figure 4

A Complex I Inhibition - PARCB

POU2F3/ASCL2 Subtype (PARCB-P3-TP5)

ASCL1 Subtype (PARCB-P7-TP6)

Oligo. FCCP Rot/AA

OCR (pmolsO₂/min/10⁴ cells)

Time (minutes)

- Control (untreated)
- Control (30 nM IACS)
- NDI1 (untreated)
- NDI1 (30 nM IACS)

B Complex I Inhibition - PARCB

POU2F3/ASCL2 Subtype (PARCB-P3-TP5)

ASCL1 Subtype (PARCB-P7-TP6)

Cell doublings (72 hr)

NDI1 OE   −   −   +   +
30 nM IACS   −   +   −   +

C mt-DNA Transcription Inhibition - PARCB

POU2F3/ASCL2 Subtype (PARCB-P3-TP5)

ASCL1 Subtype (PARCB-P7-TP6)

Cell doublings (96 hr)

[IMT1B] (μM)   0   0.1   0.5   1.0   2.0

D OXPHOS Gene Deletion (CRISPR KO) - Lung Cancer

PC2 (2.5%)

PC1 (3.68%)

- ● SCLC ● LUAD ■ LUCA
- ★ SCLC ▼ LUSQ

NSCLC (PC1-High) ← → SCLC (PC1-Low)

OXPHOS
Adipogenesis
G2M Checkpoints
Glycolysis
MYC Targets V2
Protein Secretion
MTORC1 Signaling
Androgen Response
TGF Beta Signaling
PI3K AKT MTOR

NES

Pos. Enrich. q<0.05

Neg. Enrich. q<0.05

Figure 5

A PARCB tumor-Derived cell lines — PGC-1α O.E. — Seahorse Respirometry — SQ Injection — PET/CT Imaging and Histology In Tumors

POU2F3/ASCL2 Subtype
ASCL1 Subtype

Day -14 — Day -7 — Day 0 — Day 28

PET Probes
Glucose — Glut1 — ^{18}F-FDG
Glucose
Pyruvate — Lactate
^{18}F-BnTP
Mitochondrion

B

POU2F3/ASCL2 subtype

OCR (Normalized to Control) vs Time (minutes)
Oligo. FCCP Rot/AA
Basal Respiration — Maximal Respiration

PGC-1α O.E. (PARCB-P3-TP5)
Control (PARCB-P3-TP5)

ASCL1 subtype

OCR (Normalized to Control) vs Time (minutes)
Oligo. FCCP Rot/AA
*** Basal Respiration — *** Maximal Respiration

PGC-1α O.E. (PARCB-P7-TP6)
Control (PARCB-P7-TP6)

C

POU2F3/ASCL2 — ASCL1

Tumor Volume (mm³)

PARCB+PGC-1α
PARCB+Control

D ^{18}F-FDG microPET/CT

PET CT PET/CT
%ID/cc 20 / 0

^{18}F-FDG (%ID/cc)

PARCB+PGC-1α
PARCB+Control

E ^{18}F-BnTP microPET/CT

PET CT PET/CT
%ID/cc 20 / 0
Inset %ID/cc 3 / 0

^{18}F-BnTP (%ID/cc)

PARCB+PGC-1α
PARCB+Control

Figure 6

Figure 7

A PARCB - POU2F3/ASCL2 subtype
Chen et al. 2023

B In Vitro SCN Prostate Cancer Transformation
Li et al. 2024

C C4-2B + PRNBSAN
Li et al. 2024

D C4-2B + PRNBSAN
Li et al. 2024

E ASCL1 ChIP-Seq