RNAseq reveals that *Pseudomonas aeruginosa* mounts medium-dependent competitive

responses when sensing diffusible cues from *Burkholderia cenocepacia*

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Abstract

Most habitats on earth are colonized by diverse bacterial communities, offering ample opportunities

for inter-species interactions. While competition for space and nutrients might often dominate such

interactions, little is known about whether bacteria can sense competitors and mount specific

responses to withstand their attacks. The competition-sensing hypothesis proposes that bacteria can

do so through nutrient stress and cell damage cues. Here, we conducted a replicated RNAseq-

transcriptomic study to test this hypothesis. We exposed *Pseudomonas aeruginosa* to either its own

spent medium or to the supernatant of its competitor *Burkholderia cenocepacia*. Compared to

controls, we detected significant changes in the transcriptome of *P. aeruginosa* that entail both general

responses to spent medium and specific responses to the competitor. Specifically, genes encoding

various competitive traits, including the type-VI secretion system, the siderophore pyoverdine, and the

toxins phenazines and hydrogen cyanide, were upregulated when exposed to the competitor

supernatant. Similarly, several genes coding for stress response and quorum-sensing regulators were

overexpressed. Moreover, we found transcriptional responses to vary as a function of iron availability,

whereby metabolically more costly responses were launched under iron rich conditions. Altogether,

our results reveal nuanced competitive responses of *P. aeruginosa* when exposed to *B. cenocepacia*

supernatant, integrating both environmental and social cues.

Introduction

Sequencing technologies have revealed that natural bacterial communities are incredibly diverse, and that myriads of taxa can live in close proximity to one another [1–3]. From an ecological perspective, the living together of completely different species must ultimately lead to intense inter-specific competition for essential resources such as nutrients, space and oxygen [4–6]. This view is supported by the fact that many bacterial species have evolved mechanisms to attack and defend themselves from competitors [7,8]. Defensive strategies include the formation of protective biofilms, motility to move away from competitors or the use of efflux pumps to eject toxic compounds [9–14]. Attacking measures typically involve toxins that are either secreted in the environment, or directly injected into competitor cells via contact-dependent secretion systems [8,15–23].

There has recently been much interest in understanding whether and how bacteria can sense the presence of competitors and mount adequate responses [24–31]. This interest roots in the evolutionary thinking that defensive and attacking responses are costly and should only be mounted when required. Cornforth and Foster [24] developed a concept for competition sensing by proposing that bacteria rely on cues such as resource limitation or competitor-induced cell damage, to trigger competitive counter measures such as toxin production and biofilm formation. Moreover, it was proposed that bacteria might be able to sense competitors via their secreted diffusible molecules, such as toxins or quorum-sensing molecules, to mount responses before they physically meet the competitor [25,27].

Here we used transcriptomics to test whether *P. aeruginosa* PAO1 [32] changes its gene expression profile when exposed to the supernatant of a competitive species, *B. cenocepacia* H111, containing secreted compounds that could serve as cues for competition sensing. We chose these two bacteria as a model system because both species are opportunistic human pathogens, which can co-infect lungs of cystic fibrosis patients, but potentially also co-exist in natural soil habitats [33–39]. We thus reasoned that *P. aeruginosa* might have evolved ways to sense and respond to diffusible cues from *B. cenocepacia*. To test our hypothesis, we exposed *P. aeruginosa* to spent supernatant from *B.*

cenocepacia cultures mixed with fresh medium and compared its transcriptome to conditions where

it grew in fresh medium alone or when exposed to its own supernatant (Fig. 1). We carried out this

setup in three-fold replication under both iron-rich and iron-limited conditions. We then used the

replicated transcriptomic data (n = 18) to perform the following main analyses. First, we compared the

transcriptomes of *P. aeruginosa* growing in iron-rich versus iron-limited CAA medium without

supernatant supplementations to validate whether genes known to be iron-regulated respond to our

treatment in the expected way. Second, we conducted a global analysis to quantify the number and

type of differentially up- and downregulated genes across the supernatant treatments in the two

nutrient environments. Third, we focused on specific gene classes encoding competitive traits and

regulators that could potentially be involved in competition sensing and tested whether they are

differentially expressed when *P. aeruginosa* is exposed to the supernatant of *B. cenocepacia*.

Results

***P. aeruginosa* transcriptomes segregate in response to supernatant treatment and iron availability**

We grew *P. aeruginosa* in 100% fresh CAA medium (SN.No) and in 70% fresh CAA medium

supplemented with either 30% of its own spent supernatant (SN.Pa) or 30% of the spent supernatant

of its competitor *B. cenocepacia* (SN.Bc). The three growth treatments were carried out under both

iron-rich and iron-limited conditions (Fig. 1). Across the six conditions and the three replicates per

condition, we could map between 4 595 376 and 8 827 668 reads to the PAO1 genome (Table S1).

Based on these reads, we conducted a principal component analysis (PCA) using the rlog transformed

and normalized raw counts data [40]. We found that the first three principal components (PC)

explained 75.2 % of the total variance observed (Fig. 2A+B). While PC1 reveals a clear separation

between the cultures growing under iron-rich versus iron-limited conditions, PC3 shows segregation

between cultures growing in 100% CAA medium and cultures that received spent supernatant in

addition to 70% CAA. We further observed that the triplicates of the same treatment clustered

together, demonstrating that our independent biological replicates yielded reproducible results. The

strong clustering of replicates and the distinct differences in the transcriptomes between iron-rich and

iron-limited conditions also emerged in a Euclidean distance matrix analysis (Fig. 2C).

Expression of siderophore genes and other iron-regulated genes respond to iron limitation

To validate our transcriptomic data, we tested whether genes known to be regulated by iron

availability responded in the expected way in our conditions where bacteria grew in plain CAA medium

(iron-limited versus iron-rich) without the addition of supernatants (Fig. 3). We first focused on the

genes involved in the synthesis, secretion and regulation of the two iron-scavenging siderophores

pyoverdine and pyochelin [41–43]. As expected, we observed that all the siderophore genes were

significantly upregulated under iron limitation. The expression of *toxA* and *prpL* (*piv*), encoding

exotoxinA and protease IV, which are known to be induced in the presence of pyoverdine [44,45], were

also significantly upregulated under iron limitation. Next, we focused on two genes encoding the

superoxide dismutase SodB (iron-dependent) and SodM (manganese-dependent). We observed that

sodB is downregulated, whereas *sodM* is upregulated under iron limitation, a pattern that is in line

with the transcriptional switch described by Bollinger et al. [46]. Finally, we examined the genes

involved in hydrogen cyanide synthesis, which is controlled by the ANR regulator featuring an iron-

sulfur cluster [47,48]. Consistent with previous work, we found that *anr* expression itself was not

affected by iron availability, but the expression of *hcnABC* decreased under iron limitation. These

control analyses confirm that our RNA-Seq analysis yields reliable results. Finally, we also measured

the production of the siderophore pyoverdine over time as a key phenotype affected by iron

availability. Consistent with our transcriptomic data, we found higher levels of pyoverdine production

in iron-limited compared to iron-rich conditions (Fig. S2). In line with previous work, we further

observed that *P. aeruginosa* down-scaled *de novo* pyoverdine production when growing in its own

supernatant, which already contains pyoverdine [49].

114   ***P. aeruginosa* shows multiple distinct changes in gene expression when exposed to the supernatant**

115   **of *B. cenocepacia***

116   Next, we examined differential gene expression of *P. aeruginosa* between our three growth conditions

117   (SN.No, SN.Pa and SN.Bc), separately for iron-rich and iron-limited conditions (Fig. 4). We considered

118   a gene to be differentially expressed with log2-fold change values > 1 or < -1 and with FDR-adjusted p-

119   values < 0.05. While 5570 open reading frames were originally annotated in the *P. aeruginosa* PAO1

120   genome [50], this number has gone up to 5713 as of today, according to the *Pseudomonas* Genome

121   Database (pseudomonas.com) [51]. Our RNA-Seq analysis revealed that > 98% of these predicted

122   genes were expressed (Table S2). Across all pairwise comparisons, between 5.7% and 10.7% of the

123   genes were differentially expressed, of which on average 3.3% and 4.4% were up- and downregulated,

124   respectively (Table S2). The Venn diagrams in Fig. 4A+B show the number of differentially expressed

125   genes that are unique or shared across the growth conditions.

126   We then compared the gene expression profile of *P. aeruginosa* cells grown with *B.*

127   *cenocepacia* supernatant (SN.Bc) to the no (SN.No) and own (SN.Pa) supernatant condition. We had

128   four comparisons in total (SN.Bc vs. SN.No and SN.Bc vs. SN.Pa in both iron-limited and iron-rich

129   medium), and we show the MA plots (Fig. 4C-F), a functional classification of the differentially

130   regulated genes (Fig. 4G-J), and the top 50 up- and downregulated genes (Table S3-S6) for all four

131   comparisons. We observed more gene categories to be significantly up- or downregulated in the SN.Bc

132   vs. SN.No comparison than in the comparison between the two supernatant conditions (SN.Bc vs.

133   SN.Pa). This finding agrees with our observation that the SN.Bc and SN.Pa conditions are close to one

134   another in the PCA plot (Fig. 2) and that only a relatively small number of genes were differentially

135   regulated genes in this comparison (Fig. 4 A+B).

136   When focusing on the SN.Bc vs. SN.No comparison (showing more pronounced differences),

137   we found four defined gene categories to be significantly upregulated under iron-rich conditions (Fig.

138   4G): (E) amino acid transport and metabolism, (I) lipid transport and metabolism, (P) inorganic ion

139   transport and metabolism, and (Q) secondary metabolite biosynthesis transport and catabolism.

Especially the differential regulation of secondary metabolite genes is interesting as they often encode

competitive traits. Indeed, the table of the top 50 differentially regulated genes (Table S3) features

secondary metabolite genes involved in pyoverdine, rhamnolipid, phenazine and type-VI secretion

system (T6SS) synthesis. Under iron-limited conditions, seven gene categories were significantly

upregulated (Fig. 4I). The categories predominantly involve metabolism: amino acids (E), nucleotides

(F), carbohydrates (G), coenzymes (H), lipids (I); but also energy conversion (C) and transcription (K).

These results suggest that *P. aeruginosa* accelerates metabolic activities as a major competitive

response against *B. cenocepacia* under iron-limiting conditions.

Beyond these global analyses, two observations in Tables S3-S6 caught the eye. First, genes of

the PA0878-PA0883 cluster were among the topmost upregulated genes in iron-rich conditions (Tables

S3 and S5). These genes encode enzymes involved in the degradation of mesaconate and itaconate

[52,53]. The two acids show antimicrobial activities and are produced by macrophages but also certain

bacteria through the glutamate metabolism pathway [54,55]. The upregulation of these genes could

thus represent a defensive response against an unknown antibacterial compound in the supernatant.

Second, genes of the clusters PA5081-PA5086 and PA1343-1334 were among the topmost upregulated

genes in iron-limited conditions (Tables S4 and S6). These genes encode proteins involved in the

utilization of D-glutamic acid (D-Glu) and D-glutamine (D-Gln), two essential components of the

bacterial cell wall [56]. Their upregulation could potentially be a response to cell wall damage induced

by compounds secreted by *B. cenocepacia*.

***P. aeruginosa* upregulates competitive traits when exposed to the supernatant of *B. cenocepacia* in**

a medium-specific manner

We further focused on gene clusters encoding traits that are known to be involved in inter-species

interactions and tested whether they are differentially regulated upon exposure to *B. cenocepacia*

supernatant. Our list of 407 genes covers a broad spectrum of putatively competitive traits, including

secretion systems, efflux pumps, siderophores, toxins, motility, adhesion and biofilm components (Fig.

5 + Table S7). Numbers and names of all genes together with their log2-fold changes and adjusted p-

values are listed in Table S8 (SN.Bc vs. SN.No) and Table S9 (SN.Bc vs. SN.Pa). We tested whether gene

clusters were significantly up- or downregulated. We argue that relevant gene clusters should be

differentially regulated in both comparisons to be considered as specific responses of *P. aeruginosa* to

the supernatant of *B. cenocepacia*. Conversely, gene clusters that are only upregulated in the SN.Bc vs.

SN.No, but not in the SN.Bc vs. SN.Pa comparison more likely reflect general responses to spent media.

In iron-rich conditions, gene clusters encoding T6SS were significantly upregulated in both

comparisons (Fig. 5A+B & Table S10). The T6SS is a speargun-type of weapon deployed against other

gram negatives [22]. *P. aeruginosa* has three T6SS clusters and a closer inspection of the data revealed

that only two of the three clusters (HSI-I and HSI-II) were significantly upregulated (Table S8+S9).

Furthermore, the gene cluster encoding synthesis and transportation of the siderophore pyoverdine

was also significantly upregulated in both comparisons (Fig. 5A+B & Table S10). Pyoverdine can induce

iron starvation in competitors like *B. cenocepacia* that lack the receptor for pyoverdine uptake [29]

and increased production of this siderophore can be considered a competitive response [57]. In

contrast, the gene cluster encoding efflux pumps and phenazines were significantly downregulated in

both comparisons (Figure 5A+B). While efflux pumps can be used to expel toxic compounds from the

bacterial cell [14], phenazines are broad-spectrum toxins that are also involved in redox reactions [58].

In iron-limited conditions, the observed gene regulatory responses of *P. aeruginosa* to *B.*

cenocepacia supernatant were completely different. Here, the gene clusters encoding phenazines and

hydrogen cyanide, two groups of bacterial toxins, were significantly upregulated in both comparisons

(Figure 5C+D & Table S10). Moreover, several gene clusters were significantly downregulated in both

comparisons, including the ones encoding the T1SS, synthesis and transportation of the siderophore

pyochelin, the production of pyocin toxins, and the production of motility (flagella, rhamnolipids, pili)

as well as biofilm structures (exopolysaccharides) (Figure 5A+B & Table S10). Taken together, our

results indicate that *P. aeruginosa* adjusts its competitive strategy according to iron availability.

General stress response, quorum sensing, and two-component systems are involved in competition sensing

Finally, we focused on potential regulatory elements guiding competition sensing (Table S7-S9). We followed Cornforth & Foster [24] who highlighted three potential competition sensors: (i) general stress response components, (ii) quorum-sensing systems, and (iii) two-component signaling systems. The three categories are not mutually exclusive. Here, we keep all the two-component signaling systems together, even though some of them (e.g. *gacS*) are involved in the general stress response [59,60]. In Fig. 6, we plot the log2-fold changes of 93 genes belonging to these three classes in *P. aeruginosa*. Tags and names of all genes together with their log2-fold changes and adjusted p-values are listed in Table S8 (SN.Bc vs. SN.No) and Table S9 (SN.Bc vs. SN.Pa). We contrasted the log2-fold changes of the comparison SN.Bc vs. SN.No against the comparison SN.Bc vs. SN.Pa to identify stress response and regulatory genes that were significantly up (+) or down (-) regulated in both comparisons.

In iron-rich conditions (Fig. 6A), we found nine such genes, including the general stress response components *rpoS* (+) and *sodB* (-); the quorum-sensing genes *rhlR* (-), *rhlI* (-) and *lasI* (-); and the two-component signaling systems *retS* (+), *narX* (+), *dctB* (+), and *parS* (-). In iron-limited conditions (Fig. 6B), we found another set of three elements that were differentially regulated when *P. aeruginosa* was exposed to the supernatant of *B. cenocepacia*, namely *pqsA* (+), *ercS* (+), and PA3271 (+). Our analysis identifies several candidate regulatory elements that could steer competition sensing, but we also find that the candidate elements differ between iron-rich and iron-limited conditions.

Discussion

Bacteria commonly live in diverse communities, be it in environmental habitats, in infections or in host-associated microbiomes [1,2,61]. It has increasingly been recognized that bacteria interact in these communities, with interactions covering the entire range of the social spectrum, from cooperation to commensalism to competition [4,5]. While competition for space and nutrients seems ubiquitous, the question is whether bacteria preemptively deploy competitive traits, or whether they have evolved

mechanisms to sense competitors and to mount responses when needed. The latter scenario is

captured by the competition-sensing hypothesis [24], proposing that bacteria can use cues such as

nutrient stress and competitor-induced cell damage to launch competitive responses. Here we tested

this hypothesis and asked whether competition sensing is detectable at the transcriptional level in *P.*

aeruginosa exposed to either its own spent medium or the supernatant of its competitor *B.*

cenocepacia. Our results reveal large-scale changes in the transcriptome of *P. aeruginosa*, entailing

both general responses to spent medium and specific responses to the competitor. Specifically, we

found genes for several competitive traits, including the T6SS, pyoverdine, phenazines, hydrogen

cyanide, and putative antibacterial (e.g. itaconate/mesaconate) degrading enzymes to be upregulated

upon exposure to the competitor supernatant. We further identified several genes encoding

regulatory elements (general stress response, quorum sensing and two-component signaling systems)

that are increasingly expressed with competitor supernatant. Moreover, transcriptional and

competitive responses varied as a function of iron availability. Altogether, our results support the

competition-sensing hypothesis by revealing nuanced responses of *P. aeruginosa* to *B. cenocepacia*

supernatant, integrating both environmental and social information.

Transcriptomic studies, such as ours, reveal correlations between experimental treatments

and shifts in gene expression patterns. They do not necessarily allow to draw direct conclusions of how

exactly competition sensing works and whether changes observed are indeed caused by competitors

and reflect evolutionary adaptations. Furthermore, transcriptional analysis does not take translational

regulations at the protein level into account. Nonetheless, our study revealed several notable shifts in

gene expression, which we wish to discuss in the context of the competition-sensing hypothesis at

three different levels: (i) responses to own spent medium versus supernatant of competitor; (ii) iron-

dependent responses; and (iii) regulatory elements that could steer competition sensing.

The competition-sensing hypothesis postulates that bacteria can sense competitors in two

different ways: indirectly via the sensing of nutrient limitation or directly via cell damage induced by

the competitor itself or its secreted molecules. Our study design allows us to partially differentiate

between the two scenarios. Specifically, the SN.Bc vs. SN.No comparison captures both nutrient

limitation (30% spent medium) and cell damage (via diffusible molecules), whereas the SN.Bc vs. SN.Pa

comparison filters out limitations for basic nutrients such as carbon and nitrogen, as both treatments

entail spent media. Given this setup, we identified genes of four competitive traits that were

upregulated in both comparisons, suggesting that these changes reflect direct responses to the *B.*

cenocepacia supernatant. Among the upregulated genes in iron-rich conditions, there were two T6SS

clusters (HSI-I and HSI-II) and genes encoding the synthesis/transportation machinery of the

siderophore pyoverdine (Fig. 5A+B), whereas in iron-limited conditions genes encoding the synthesis

of phenazines and hydrogen cyanide were upregulated (Fig. 5C+D). T6SS, phenazines and hydrogen

cyanide are well-known broad-spectrum weapons of *P. aeruginosa* against competitors [8]. Pyoverdine

can also be a competitive agent since this strong siderophore can withhold iron from competitors such

as *B. cenocepacia* [57,62]. There were also changes in gene expression that can primarily be attributed

to nutrient limitation because they were only upregulated in the SN.Bc vs. SN.No comparison. The

affected genes encode the synthesis/transportation machinery of the siderophore pyochelin under

iron-rich condition (Fig. 5A), and several classes of metabolic genes under iron-limited conditions (Fig.

4I). In the light of the competition-sensing hypothesis, these patterns suggest that both nutrient

limitation and competitor-induced cues have likely contributed to the observed gene expression

changes.

We found that the putative competition-sensing responses in *P. aeruginosa* markedly differed

between iron-rich and iron-limited conditions. Under iron-rich conditions, we observed the

upregulation of T6SS and pyoverdine genes (Fig. 5B), whereas phenazines and hydrogen cyanide genes

were upregulated under iron-limited conditions (Fig. 5D). We propose that these differential responses

are the result of the different production costs associated with the respective competitive traits. T6SS

is a complex structure comprising many different proteins and is likely costly to produce [63].

Pyoverdine is also costly to produce since it involves a complex non-ribosomal peptide synthesis

machinery that needs to be built up [64]. Conversely, phenazines and hydrogen cyanide are relatively

simple molecules and only few enzymes are required for their synthesis, which means that they are

comparatively cheap to make [58,65]. Thus, our finding suggests that *P. aeruginosa* invests into costly

competitive traits in nutrient (e.g. iron) rich environments, whereas the bacteria switch to cheaper

competitive traits when essential nutrients, such as iron, are limited. The idea that *P. aeruginosa*

follows a cost-saving strategy is further supported by our observation that genes for several

competitive traits are downregulated (T1SS, pyochelin, pyocins, motility, biofilm formation) under

iron-limited conditions (Fig. 5C+D). Conversely, we observed that several classes of metabolic genes

were significantly upregulated under iron-limited conditions (Fig. 4I). Accelerated metabolic activities

is a form of nutrient competition, and our data thus indicate that *P. aeruginosa* rather invests in

nutrient than in costly interference competition mechanisms when iron is limited.

The competition-sensing hypothesis predicts that general stress response and regulators

detecting nutrient limitation and cell damage should be involved in the process [24,30]. We indeed

found that several genes involved in the general stress response [66,67] and two-component signaling

systems [59,60,68] were significantly differentially regulated in both the SN.Bc vs. SN.No and SN.Bc vs.

SN.Pa comparisons [iron-rich condition: *rpoS*(+), *sodB*(-), *retS*(+), *narX*(+), *dctB*(+), *parS*(-); iron-limited

condition: *ercS*(+), PA3271(+); Fig. 6]. Here, we discuss three candidates, RpoS, RetS, and ParS, where

links to competition-sensing may exist. RpoS is a sigma factor that mediates the general stress

response in *P. aeruginosa* and other bacteria [66,67]. It is involved in the regulation of protective

measures against numerous environmental stressors like high temperature, hyperosmolarity and

oxidative stress. Our finding that this key regulator is significantly upregulated in response to

competition shows that our spent supernatant treatments induced significant stress in *P. aeruginosa*.

ParS-ParR is a two-component system that reacts to cell wall damage induced by molecules such as

polymyxin B and colistin [69,70]. Detecting cell wall damage was highlighted as one of the most likely

trigger of a competition-sensing response [24], which seems to be corroborated by our finding. The

ParS-ParR system works both as activator and repressor [70], such that the observed down-regulation

of *parS* could trigger the expression of an otherwise repressed trait. However, it remains unclear

whether the ParS-ParR system is a repressor to any of the upregulated traits in our study. Finally, RetS

is a repressor of the GacA/S two-component regulatory system [71]. As such, it represses biofilm

formation and activates T6SS synthesis [26]. The latter matches our finding that genes encoding the

T6SS were significantly upregulated. RetS is induced in response to cell lysis by kin cells and is thus a

sensor for cell death, which is (similar to ParS) in support of the idea that cell damage forms the basis

of competition sensing.

In contrast to iron-rich conditions, we found few stress-related regulatory candidates that

could be involved in competition sensing under iron-limited conditions (Fig. 6B). Instead, we found

that several genes of the PQS quorum-sensing system were significantly upregulated, particularly in

the SN.Bc vs. SN.Pa comparison. The PQS quorum-sensing system directly controls the expression of

phenazines and hydrogen cyanide. The increased activity of PQS genes thus matches our observation

that phenazine and hydrogen cyanide genes were overexpressed. Interestingly, quorum sensing was

proposed to feed into competition sensing cascades [24,72] and our finding now lend support to this

hypothesis. How the connection between quorum- and competition-sensing works yet remains an

open question.

In summary, our study adds to the growing body of evidence that bacteria can sense

competitors and mount specific responses to fight and withstand them [24,29–31]. Our findings

further indicate that *P. aeruginosa* reacts to both nutrient limitation and compounds secreted by the

competitor *B. cenocepacia*. Another relevant insight is that the transcriptional responses observed are

not uniform but highly specific to iron (nutrient) availability. Our study opens several new questions to

be addressed in future research. For example, it would be interesting to test whether the same

competitive traits are upregulated when *P. aeruginosa* interacts directly with *B. cenocepacia* and not

just via molecules in the supernatant. Another key point is whether *P. aeruginosa* can discriminate

between different competitors and adjust its competitive response accordingly. At the ecological level,

one might wonder how competition sensing affects species dynamics. Is competition-sensing required

to displace a competitor or simply useful to defend its niche? These questions reveal that we are only

at the beginning of understanding whether competition-sensing is a key modulator of bacterial

interactions and whether the transcriptional changes observed in our study have at least partly evolved

for the purpose of sensing competitors.

Methods

Bacterial strains and media

For all our experiments, we used the standard laboratory *P. aeruginosa* strain PAO1 (ATCC 15692) and

B. cenocepacia strain H111 (LMG 23991), an isolate from a cystic fibrosis patient [73,74]. Overnight

cultures were grown in lysogeny broth (LB). All gene-expression experiments were conducted in

casamino acids (CAA) medium (per 1 liter: 5 g casamino acids; 1.18 g $K_2HPO_4 \cdot 3H_2O$; 0.25 g $MgSO_4 \cdot 7H_2O$)

supplemented with 20 mM $NaHCO_3$ and 25 mM HEPES buffer. We induced strong iron limitation by

adding 100 μg/ml of the natural iron chelator human apo-transferrin. To create iron rich medium, we

omitted transferrin from the above recipe and added 20 μM $FeCl_3$ instead. All chemicals for the

bacterial culture media were purchased from Sigma-Aldrich, Switzerland.

Supernatant preparation from P. aeruginosa *and* B. cenocepacia *cultures*

To generate spent supernatants, we first grew cultures of *P. aeruginosa* and *B. cenocepacia* in LB

overnight at 37°C in an orbital shaker at 220 rpm. Overnights were then centrifuged at 7500 rpm for 2

minutes at room temperature, and cell pellets washed twice with 0.8% NaCl to remove spent LB

medium. We then adjusted resuspended bacteria to an optical density of 1 at 600 nm (OD_{600}) in 0.8%

NaCl. Subsequently, we inoculated 200 μl of the bacterial suspensions (*P. aeruginosa* or *B.*

cenocepacia) in 500 ml Erlenmeyer flasks containing either iron-limited or iron-rich CAA medium

(150 ml) and incubated the cultures at 37°C in an orbital shaker at 220 rpm. We had three biological

replicates for each species and iron treatment. We followed the growth of the *P. aeruginosa* and *B.*

cenocepacia monocultures by monitoring the OD_{600} over time in a spectrophotometer (Ultrospec 2100

pro, Amersham Biosciences). After reaching stationary phase (iron-limited medium: *P. aeruginosa* at

46 h; *B. cenocepacia* at 48 h; iron-rich medium: *P. aeruginosa* and *B. cenocepacia* at 17 h), the cultures

were distributed to sterile 50 ml tubes (Sarstedt) and centrifuged at 8000 rpm for 2 minutes at room

temperature. Supernatants were decanted into fresh 50 ml tubes (Sarstedt) and then sterilized using

PES membrane filters with low protein adsorption (0.22 μm cutoff) and stored in new 50 ml sterile

tubes at -80°C until further usage.

Experimental design of transcriptome study

For the main transcriptome experiment, we cultured *P. aeruginosa* under six different growth

conditions in three-fold replication (18 cultures in total) (Fig. 1). We had one additional replicate per

growth condition that we used solely to monitor growth (Fig. S1). This is important to ensure that

experimental cultures are harvested in the mid- to late-exponential phase prior to nutrient limitation

(Fig. S1). Our main treatment consisted of *P. aeruginosa* exposed to 30% of *B. cenocepacia* supernatant

mixed with 70% fresh CAA medium. 30% supernatant reflects a substantial exposure of *P. aeruginosa*

to *B. cenocepacia*, without affecting the growth of *P. aeruginosa* (Fig. S1). As control treatments, we

grew *P. aeruginosa* in either 100% fresh CAA medium, or in 70% CAA medium supplemented with 30%

P. aeruginosa supernatant. All three treatments were carried out under iron-limited and iron-rich

conditions with the supernatants being generated under the same iron treatment. We first prepared

two starter cultures of *P. aeruginosa* by inoculating 20 ml LB medium with 200 μl of a *P. aeruginosa*

overnight culture in 100 ml Erlenmeyer flasks. These starter cultures were incubated at 37°C in an

orbital shaker at 220 rpm. Once the cultures reached the late exponential growth phase, we adjusted

their OD_{600} to 1, and used one of the two starter cultures to either inoculate the 12 iron-limited or the

12 iron-rich replicates. The final medium volume was 200 ml in 1l Erlenmeyer flasks, and the initial

inoculum was $OD_{600} = 1\times10^{-2}$ (corresponding approximately to 9.10^6 cells/ml). Each replicate of the *P.*

aeruginosa and *B. cenocepacia* supernatant treatment contained a supernatant from an individually

grown *P. aeruginosa* or *B. cenocepacia* monoculture under the respective iron condition. For culture

harvesting, we followed the protocol by Pessi et al 2007 [75]. In brief, once the cultures reached the

late exponential phase, we transferred them to ice and distributed them to 50 ml tubes (Greiner)

containing 5 ml ice cold stop solution (10% phenol buffered with Tris-HCl to pH8 (Sigma-Aldrich,

Switzerland) and 90% ethanol). We mixed the suspension by manual inversion of tubes followed by

centrifugation at 4°C for 5 minutes at 9000 rpm. We discarded the supernatant and flash-froze the cell

pellet in liquid nitrogen, which was then stored at -80°C.

RNA isolation, library preparation and RNA Sequencing

We extracted the total RNA from *P. aeruginosa* cell pellets using a modified hot acid phenol protocol

(see [75,76] for detailed protocols), followed by the removal of short RNAs, including the 5S ribosomal

RNA (5S rRNA), with the RNAeasy MiniKit (Qiagen). We completely removed the genomic DNA (gDNA)

with RQ1 RNase-Free DNase (Promega), purified the RNA with the RNAeasy MiniKit (Qiagen) and the

absence of gDNA was confirmed by a 40-cycles PCR using primers for the *rpoD* gene (rpoD_fwd:

5'CTGATCCAGGAAGGCAACAT; rpoD_rev: 5'TGAGCTTGTTGATCGTCTCG). The quality of the mRNA was

analyzed by measuring the rRNA integrity through capillary electrophoresis in a Bioanalyzer 2100

(Agilent) using the Agilent RNA 6000 Nano Chips. We used 150 ng of RNA for cDNA synthesis and library

preparation with the Encore® Complete Prokaryotic RNA-Seq DR Multiplex System from NuGEN

(NuGEN Tecan, San Carlos, USA). During the cDNA synthesis, most of the ribosomal RNA in the samples

was eliminated with the use of the insert-Dependent Adaptor Cleavage (lnDAC) technology to selective

priming. The resulting cDNA was fragmented into 200 bp fragments with a Covaris S220 AFA system

prior to the library preparation. For library preparation, we followed the protocol described by Lardi

et al. [77]. We analyzed the concentration, quality and size distribution of the libraries with capillary

electrophoresis using D1000 ScreenTapestation from Agilent (size range 100-800 bp) (Agilent

Technologies, Santa Clara, USA). Single-end 70 base-pair sequencing of the libraries was performed on

an Illumina HiSeq2500 machine at the Functional Genomics Center Zurich.

Analysis of differential gene expression

Illumina-generated sequencing reads were processed and mapped to the *P. aeruginosa* PAO1 genome sequence [50] from the *Pseudomonas* Genome Database (www.pseudomonas.com) [51] using the CLC Genomics Workbench v7.0 (QIAGEN CLC bio, Aarhus, Denmark). We only considered transcripts that could be unambiguously mapped (allowing up to two mismatches per read) to the *P. aeruginosa* genome. We excluded genes with zero read in all the compared conditions from further analysis. The RNA-seq raw data files of all analyzed samples are accessible through the GEO Series accession number GSE224821.

We used the Bioconductor package DESeq2 version 1.6.3 [40] in the R environment version 4.1.1 [78] for the analysis of differential gene expression. We used a principal component analysis (PCA) and a pairwise Euclidean distance analysis between all replicates to test whether our biological replicates cluster and whether there is segregation according to treatments. For this analyses, we included all expressed genes and used the regularized logarithm (rlog) transformation (which also normalizes for library size) from the DESeq2 package to increase the similarity of variances of genes with different read counts [40]. We used the false discovery rate (FDR) test by Benjamini and Hochberg (1995) [79] to adjust p-values to account for multiple comparisons, and considered genes to be differentially expressed when the adjusted p-value was < 0.05 and the log2-fold change was > 1 or < -1. For some genes no p-value could be assigned. That is the case when one of the three replicates constitutes an outlier, which is determined by the Cook's cutoff. In addition, only genes with large enough counts (depending on the basemean and variance of the expression of the single gene across the respective three replicates) generate sufficient statistical power to yield significant fold changes. To analyze the gene expression changes of *P. aeruginosa* in response to the supernatant of its competitor *B. cenocepacia*, we compared the treatment that involve this supernatant (i.e. SN.Bc) with control treatments (i.e. vs. SN.No or SN.Pa) either in iron-rich or iron-limited conditions. Firstly, we studied global changes in gene expression. Then, all the mapped genes were assigned to global functional categories defined according to the COG database [80,81]. By using this database, some genes have been placed in several categories while other have not been assigned at all. We used the

Fisher's Exact Test for count data to compare the number of all the expressed genes with the number

of the significantly up- or downregulated genes to highlight the functional categories in which genes

are differentially expressed between our conditions of interest. Secondly, we focused on 500 specific

genes encoding competitive traits (i.e., secretion systems, efflux pumps, siderophores, toxins, motility,

adhesion, biofilm formation) and regulators that could be potentially involved in competition sensing.

For the competitive traits, we compared the mean of the log2-fold changes for each gene classes with

the theoretical value of zero using a t-test to highlight the traits that are globally differentially

expressed in *P. aeruginosa* upon exposure to *B. cenocepacia* supernatant. Because the regulators can

be activators or inhibitors, we sought to identify regulatory genes that were significantly up- or

downregulated in our comparisons of interest (SN.Bc vs. SN.No and SN.Bc vs. SN.Pa).

Acknowledgements

We thank Stefan Wyder for help with the data analysis, Yilei Liu for support in the laboratory, and the

Functional Genomics Center Zurich (FGCZ) for support with the RNA-sequencing. This project was

funded by grants from the Swiss National Science Foundation (31003A_182499 to RK and

31003A_179322 to GP) and a pilot grant from the University of Zurich Research Priority Programme

(URPP) Evolution in Action: from genes to ecosystems (to AL).

Competing interests

The authors declare no competing interests.

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Figures

652 **Fig 1. Experimental design and workflow of our transcriptomic study.** Starter cultures of *P. aeruginosa*

PAO1 were grown under standardized conditions, harvested upon reaching the late exponential phase,

654 and prepared to seed the experimental treatments in triplicates. We had three main treatments under

both iron-limited and iron-rich conditions. Yellow (SN.No): *P. aeruginosa* grows in 100% fresh casamino

656 acid (CAA) medium. Cyan (SN.Bc): *P. aeruginosa* grows in 70% fresh CAA + 30% of spent supernatant

of its competitor *B. cenocepacia* H111. Magenta (SN.Pa): *P. aeruginosa* grows in 70% fresh CAA + 30%

658 of its own spent supernatant. Upon reaching the late-exponential growth phase, cells were pelleted

and their RNA extracted and processed for transcriptomics analysis (RNA preparation and cDNA

660 synthesis, library preparation, sequencing and gene expression analyses).

Fig. 2 Principal component and Euclidean distance analyses reveal separation between experimental

664 **conditions and clustering between biological replicates of the same condition.** (**A**) + (**B**) The first three

principal components (PC) on all transcriptomics read explain 75.2 % of all the variation observed in

666   the data set. Circles and triangles depict replicates grown under iron-limited and iron-rich conditions,

respectively. Yellow symbols: *P. aeruginosa* grown in 100% fresh casamino acid (CAA) medium

668   (SN.No). Cyan symbols: *P. aeruginosa* grown in 70% fresh CAA + 30% of spent supernatant of its

competitor *B. cenocepacia* H111 (SN.Bc). Magenta symbols: *P. aeruginosa* grown in 70% fresh CAA +

670   30% of its own spent supernatant (SN.Pa). **(C)** Pairwise Euclidean distance analysis between all

replicates, shown as a heatmap covering the scale from 0 (absolute identity, dark blue) to the

672   maximum possible discrepancy (white). PC and Euclidean distance analyses both reveal a clear

separation between replicates grown in iron-limited (FeLim) versus iron-rich (FeRich) conditions and a

674   clustering of the three replicates grown under the same supernatant condition.

Fig. 3 Gene expression analysis reveals that genes known to be iron regulated respond to iron

678   **limitation.** Log2-fold change (iron-limited versus iron-rich CAA medium) in the expression of a set of

representative genes known to be regulated in response to iron availability. The data shown are from

680   the SN.No conditions where *P. aeruginosa* was grown in 100% CAA medium without supernatants,

supplemented with either no iron or 20 μM FeCl$_3$. Data represent the means and standard deviations

682   from the three biological replicates. Yellow and grey dots depict genes that are significantly and not-

significantly differently regulated, respectively (FDR-p$_{adj}$ < 0.05). Genes are grouped according to the

684   functional unit they belong to.

Fig. 4 Global differential gene expression analysis of *P. aeruginosa* in response to the exposure to spent supernatant of its competitor *B. cenocepacia*. Transcriptomic analysis in triplicates were carried out for three different conditions: *P. aeruginosa* growing in (i) 100% casamino acid (CAA) medium (SN.No), (ii) 70% CAA + 30% of spent supernatant of *B. cenocepacia* H111 (SN.Bc), and (iii) 70% CAA + 30% of its own spent supernatant (SN.Pa). Differential gene expression analysis were performed for all three pairwise comparisons (green: SN.Bc vs. SN.No; blue: SN.Bc vs. SN.Pa; red: SN.Pa vs. SN.No),

separately for iron-rich (intense shadings) and iron-limited (faint shadings) growth conditions. Venn

694   diagrams show the number of genes that are differentially expressed in one, two or all the comparisons

for iron-rich (**A**) and iron-limited (**B**) conditions. (**C-F**) MA-plots depicting the number of significantly

696   differentially regulated genes as a function of basemean values (FDR-$p_{adj} < 0.05$ and log2-fold change

> |1|) for the comparisons involving SN.Bc. (**G-J**) Percentage of differentially regulated genes according

698   to their functional (COG) classes for the comparisons involving SN.Bc. Asterisks indicate functional

classes that are significantly up- or down-regulated based on the Fisher's Exact Test for count data

700   comparing the number of all the expressed genes with the number of the significantly up- or

downregulated genes. * p < 0.05, ** p < 0.01, *** p < 0.001.

704   **Fig. 5 *P. aeruginosa* increases the expression of certain gene clusters encoding competitive traits**

when exposed to *B. cenocapacia* supernatant in a medium-specific way. Transcriptomics analysis in

706   triplicates were carried out for three different conditions: *P. aeruginosa* growing in (i) 100% casamino

acid (CAA) medium (SN.No), (ii) 70% CAA + 30% of spent supernatant of *B. cenocepacia* H111 (SN.Bc),

708 and (iii) 70% CAA + 30% of its own spent supernatant (SN.Pa). Data shows the log2-fold change in the

gene expressions for gene clusters encoding competitive traits for two comparisons (green: SN.Bc vs.

710 SN.No; blue: SN.Bc vs. SN.Pa), separately for iron-rich (**A+B**) and iron-limited (**C+D**) growth conditions.

Each dot represents an individual gene within a cluster. Colored and grey dots depict genes that are

712 significantly and not-significantly differently regulated at the single gene level, respectively (FDR-p_{adj} <

0.05). Asterisks indicate gene clusters that are, as a group, significantly up- and downregulated,

714 according to a t-test conducted using zero as the theoretical mean (* p < 0.05, ** p < 0.01, *** p <

0.001). § All individual genes in this group are significantly upregulated, but only marginally so when

716 treated as a group. This is the result of the small number of genes (n=3) in this category and thus due

to low statistical power. The dotted vertical lines represent log2-fold change = |1|.

Fig. 6 Differential expression of regulatory systems and their potential involvement in competition sensing. Panels show, from top to bottom, the log2-fold changes of genes involved in the general stress response, quorum-sensing, and two-component signaling systems. Log2-fold gene expression changes in the comparison SN.Bc vs. SN.No are plotted against the comparison SN.Bc vs. SN.Pa for iron-rich (**A**) and iron-limited (**B**) growth conditions. Each dot depicts a regulatory gene of the corresponding class. Black dots = genes significantly differently regulated in both comparisons; grey dots = genes not significantly differentially regulated in neither of the two comparisons; green dots = genes significantly differentially regulated in the SN.Bc vs. SN.No comparison; blue dots = genes not significantly differentially regulated in the SN.Bc vs. SN.Pa comparison. Significance is based on FDR-p_{adj} < 0.05. The solid lines and shaded areas are regression lines and 95% confidence intervals respectively.