Drug-Driven Phenotypic Convergence Supports Rational Treatment Strategies of Chronic Infections

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Highlights
- Collateral sensitivity can evolve from diverse genetic and phenotypic starting points
- Collateral effects of resistance evolution converges to distinct phenotypic states
- Genetic markers associated with convergent states were linked to nfxB mutations
- nfxB mutants were eradicated in vivo from the lung of a CF patient during treatment

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In Brief
The evolution of antibiotic resistance of Pseudomonas infection in cystic fibrosis patients confers predictable sensitivities to other classes of antibiotics, suggesting new ways to optimize treatments for chronic infection.

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Drug-Driven Phenotypic Convergence Supports Rational Treatment Strategies of Chronic Infections

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SUMMARY

Chronic Pseudomonas aeruginosa infections evade antibiotic therapy and are associated with mortality in cystic fibrosis (CF) patients. We find that in vitro resistance evolution of P. aeruginosa toward clinically relevant antibiotics leads to phenotypic convergence toward distinct states. These states are associated with collateral sensitivity toward several antibiotic classes and encoded by mutations in antibiotic resistance genes, including transcriptional regulator nfxB. Longitudinal analysis of isolates from CF patients reveals similar and defined phenotypic states, which are associated with extinction of specific sub-lineages in patients. In-depth investigation of chronic P. aeruginosa populations in a CF patient during antibiotic therapy revealed dramatic genotypic and phenotypic convergence. Notably, fluoroquinolone-resistant subpopulations harboring nfxB mutations were eradicated by antibiotic therapy as predicted by our in vitro data. This study supports the hypothesis that antibiotic treatment of chronic infections can be optimized by targeting phenotypic states associated with specific mutations to improve treatment success in chronic infections.

INTRODUCTION

The emergence of drug-resistant bacteria coupled with a lack of novel structural classes of antibiotics have made antibiotic resistance one of the most eminent threats to global health (May, 2014; O’Neill, 2016). Therapeutic options and strategies are especially scarce for Gram-negative pathogens such as Pseudomonas aeruginosa (Boucher et al., 2013; Cabot et al., 2012). This versatile, opportunistic pathogen is a frequent cause of acute nosocomial infections as well as chronic infections in high-risk patient groups, such as those suffering from cystic fibrosis (CF) (MeSaros et al., 2007). CF is a recessive lethal genetic disorder among the Caucasian population that is caused by mutations in the CF transmembrane conductance regulator (CFTR) gene (Elborn et al., 2016). While intensive antibiotic treatment for the eradication of P. aeruginosa infections has been successful in young patients, eradication ultimately fails, leading to the chronic infections experienced by most adult CF patients (Folkesson et al., 2012; Gibson et al., 2003; Johansen et al., 2004). During chronic infection, antibiotic treatments can temporarily reduce airway infection and inflammation, thus extending the periods of stable disease status and maintained lung function (Fodor et al., 2012). Nevertheless, the ability of P. aeruginosa to sustain chronic infection and resist antibiotic treatment is associated with decline in lung function, respiratory failure, and death in CF patients (Hauser et al., 2011; Pittman et al., 2011; Taylor-Robinson et al., 2012).

The antibiotic resistance of P. aeruginosa is driven by several factors in CF patients, including the activation of chromosomally encoded resistance mechanisms, such as decreased production of the outer membrane porin, inducible chromosomal β-lactamase AmpC, and overexpression of several efflux systems (Lister et al., 2009; Marvig et al., 2015a). The main efflux pumps are tripartite systems consisting of a resistance nodulation cell division (RND) transporter, a membrane fusion protein (MFP), and an outer membrane factor (OMF). MexAB-OprM, MexCD-OprJ, MexEF-OprN, and MexXY-OprM are the main efflux pumps that expel functionally and structurally dissimilar antibiotics (Li et al., 2015).

When Escherichia coli and Staphylococcus aureus evolve resistance toward specific antibiotics, they also develop sensitivity toward other antibiotics (Baym et al., 2016; Imamovic and Sommer, 2013; Lázár et al., 2013; Munck et al., 2014; Rodriguez de Evgrafov et al., 2015). This observation led to the proposal of a new, rational drug treatment paradigm termed collateral sensitivity cycling, in which sequential drug treatments are designed to exploit collateral sensitivity resulting from resistance evolution (Imamovic and Sommer, 2013). Collateral sensitivity has also been demonstrated in cancer cell lines (Hall et al., 2009) and was recently successfully deployed for treatment of Ph(+) acute lymphoblastic leukemia in an animal model (Zhao et al., 2016).

Collateral sensitivity may be particularly useful for optimizing treatments of chronic infections since their nature and severity warrants and requires tailored treatment strategies. Chronic lung infections of CF patients caused by P. aeruginosa may be
a useful clinical model to study the evolution of collateral sensitivity in response to antibiotic therapy. While a recent study reported a lack of collateral sensitivity in clinical isolates from CF patients (Jansen et al., 2016), the study did not investigate relative changes in strain susceptibility, and, thus, collateral sensitivity might be missed due to the lack of appropriate baseline controls. Moreover, if evolutionary tradeoffs, such as collateral sensitivity, do not occur \textit{in vivo}, then ever-increasing resistance would be the consequence of decades of antibiotic exposure. Yet, previous phenotypic characterization of CF isolates did not observe such monotonic increase in antibiotic resistance over time (López-Causapé et al., 2013). Accordingly, we hypothesized that \textit{P. aeruginosa} might evolve collateral sensitivity in response to antibiotic exposure both \textit{in vitro} and in patients and that these vulnerabilities modulate population dynamics during antibiotic treatment.

**RESULTS**

**Complex Networks of Collateral Sensitivity and Collateral Resistance**

To elucidate the collateral sensitivity network of drug-resistant strains of \textit{P. aeruginosa}, PAO1 were experimentally evolved in media that resembled the chemical composition encountered in the lungs of CF patients (SCFM) (Palmer et al., 2007). Twenty-four clinically relevant antibiotics that included anti-pseudomonal antibiotics and other drugs were chosen from eight chemical classes affecting different targets in \textit{P. aeruginosa} (Table 1). To exclude possible effects on resistance phenotypes from adaptation to novel growth conditions, we adapted the ancestral PA01 strain to SCFM for 10 days as a media control (WTE). At the last day of the adaptive evolution experiment, all lineages could grow in the media with antibiotic concentrations exceeding the clinical breakpoint defined by EUCAST for \textit{P. aeruginosa} (Table 1; Figures S1 A–S1F) (EUCAST, 2016). Collateral sensitivity or collateral resistance was defined as a decrease or increase in the MIC (minimal inhibitory concentration) of the antibiotic-resistant strain relative to the wild-type adapted to SCFM (WTE) (Imamovic and Sommer, 2013). To confirm the robustness of our susceptibility tests, we measured the significance of the fold increase or decrease in resistance relative to the WTE (see STAR Methods). We observed that collateral sensitivity toward ampicillin decreased by 8.5-fold for ciprofloxacin-resistant strain (p value $3.42 \times 10^{-21}$, t test). Increase in susceptibility for other antibiotics such as amikacin and colistin.

### Table 1. List of Antibiotics Used in the Study

<table>
<thead>
<tr>
<th>Antibiotic</th>
<th>Antibiotic Abbreviation</th>
<th>Class (sub-class)</th>
<th>Class Abbreviation</th>
<th>Target</th>
<th>EUCAST Breakpoints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amikacin</td>
<td>AMI</td>
<td>aminoglycoside A</td>
<td>protein synthesis</td>
<td>30S</td>
<td>16</td>
</tr>
<tr>
<td>Gentamicin</td>
<td>GEN</td>
<td>aminoglycoside A</td>
<td>protein synthesis</td>
<td>30S</td>
<td>4</td>
</tr>
<tr>
<td>Tobramycin</td>
<td>TOB</td>
<td>aminoglycoside A</td>
<td>protein synthesis</td>
<td>30S</td>
<td>4</td>
</tr>
<tr>
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<td>quinolone Q</td>
<td>DNA gyrase</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Levofloxacin</td>
<td>LEV</td>
<td>quinolone Q</td>
<td>DNA gyrase</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>Ampicillin</td>
<td>AMP β-lactam (penicillin)</td>
<td>B</td>
<td>cell wall</td>
<td></td>
<td>n.a.</td>
</tr>
<tr>
<td>Piperacillin</td>
<td>PIP β-lactam (penicillin)</td>
<td>B</td>
<td>cell wall</td>
<td></td>
<td>16</td>
</tr>
<tr>
<td>Carbenicillin</td>
<td>CAR β-lactam (penicillin)</td>
<td>B</td>
<td>cell wall</td>
<td></td>
<td>n.a.</td>
</tr>
<tr>
<td>Ticarcillin</td>
<td>TIC β-lactam (penicillin)</td>
<td>B</td>
<td>cell wall</td>
<td></td>
<td>16</td>
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<tr>
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<td>AZE β-lactam (monobactam)</td>
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<td>cell wall</td>
<td></td>
<td>16</td>
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<tr>
<td>Ceftiraxime</td>
<td>CFR β-lactam (cephalosporin)</td>
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<td>cell wall</td>
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<td>8</td>
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<tr>
<td>Ceftazidime</td>
<td>CFZ β-lactam (cephalosporin)</td>
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<td>cell wall</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>Meropenem</td>
<td>MER β-lactam (carbapenem)</td>
<td>B</td>
<td>cell wall</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>Imipenem</td>
<td>IMI β-lactam (carbapenem)</td>
<td>B</td>
<td>cell wall</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>Minocycline</td>
<td>MIN tetracycline T</td>
<td>tetracycline T</td>
<td>protein synthesis</td>
<td>30S</td>
<td>n.a.</td>
</tr>
<tr>
<td>Doxycycline</td>
<td>DOX tetracycline T</td>
<td>tetracycline T</td>
<td>protein synthesis</td>
<td>30S</td>
<td>n.a.</td>
</tr>
<tr>
<td>Azithromycin</td>
<td>AZY macrolide M</td>
<td>macrolide M</td>
<td>protein synthesis</td>
<td>50S</td>
<td>n.a.</td>
</tr>
<tr>
<td>Erythromycin</td>
<td>ERI macrolide M</td>
<td>macrolide M</td>
<td>protein synthesis</td>
<td>50S</td>
<td>n.a.</td>
</tr>
<tr>
<td>Clarithromycin</td>
<td>CLA macrolide M</td>
<td>macrolide M</td>
<td>protein synthesis</td>
<td>50S</td>
<td>n.a.</td>
</tr>
<tr>
<td>Colistin</td>
<td>COL polymyxin P</td>
<td>polymyxin P</td>
<td>lipopolysaccharide</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Fosfomycin</td>
<td>FOS fosfomycin F</td>
<td>fosfomycin F</td>
<td>cell wall biogenesis</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td>Rifampicin</td>
<td>RIF rifamycin R</td>
<td>rifamycin R</td>
<td>RNA synthesis</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td>Trimethoprim/</td>
<td>TMS antifolate C</td>
<td>antifolate C</td>
<td>combination folic acid pathway/ synthesis of dihydrofolic acid</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td>Sulfamethoxazole</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

n.a., no EUCAST breakpoints listed (EUCAST, 2016).
we observed collateral sensitivity in 64% of the evolved antibiotic-resistant PAO1 strains. Color coding represents the fold increase (red) or decrease (blue) in MIC value relative to the PAO1 strain evolved in SCFM media without antibiotics (WTE). For each strain, five replicates dose-response curves were performed to determine the drug susceptibility (Table S1). The order of the drugs and resistant strains was determined by hierarchical clustering using the similarity of normalized MIC values as the distance measure.

Given that the majority of resistant strains (75%) were collateral sensitive to at least one antibiotic (Figure 1A; Table S1), we were able to construct a collateral sensitivity network for P. aeruginosa (Figures 1B and S2A). We simulated the number of collateral sensitivity cycles comprising: (1) all antibiotics used in the study (Table S2). For EUCAST-defined anti-pseudomonal drugs (EUCAST) versus all drugs used in the study (Table S2).

Figure 1. Consequence of Drug Resistance Evolution: Collateral Sensitivity and Collateral Resistance

(A) Heatmap represents quantification of collateral sensitivity profiles of the 24 evolved antibiotic-resistant PAO1 strains. Color coding represents the fold increase (red) or decrease (blue) in MIC value relative to the PAO1 strain evolved in SCFM media without antibiotics (WTE). For each strain, five replicates dose-response curves were performed to determine the drug susceptibility (Table S1). The order of the drugs and resistant strains was determined by hierarchical clustering using the similarity of normalized MIC values as the distance measure.

(B) Sub-network of collateral interactions among drugs commonly administered in treatments of CF patients. For collateral susceptibility networks, the directed path of each arrow represents the collateral sensitivity (blue) or collateral resistance (red) of an affected variable (drug-resistant strain) on the causal variable (drug). Collateral sensitivity cycling for two drugs would consist of alternating application of two drugs with collateral sensitivity (e.g., colistin and aztreonam) (full network for collateral sensitivity and resistance interaction depicted in Figures S2A and S2B).

(C) Number of possible collateral sensitivity cycles with anti-pseudomonal drugs (EUCAST) versus all drugs used in the study (Table S2). See also Figures S1 and S2.

was 2.5- and 1.5-fold relative to the WTE; yet, in both cases, we observed that collateral sensitivity observed was statistically significant (p value $7.87 \times 10^{-5}$ and $2.07 \times 10^{-9}$, t test, respectively) (Figure S1J).

Given that the majority of resistant strains (75%) were collateral sensitive to at least one antibiotic (Figure 1A; Table S1), we were able to construct a collateral sensitivity network for P. aeruginosa (Figures 1B and S2A). We simulated the number of collateral sensitivity cycles comprising: (1) all antibiotics used in the study (Table S2). For EUCAST-defined anti-pseudomonal drugs, we detected five collateral sensitivity cycles including two and three drugs (Figure 1C; Table S2). However, expanding the simulation for collateral sensitivity cycles to all antibiotics tested, the majority of antibiotics exhibiting collateral sensitivity (78%) could be employed in collateral sensitivity cycling. The number of simu-
to exploit specific vulnerabilities of *P. aeruginosa* that result even from management of other pathogens.

**Evolution of Drug Resistance Leads to Phenotypic Convergence toward Collateral States**

To systematically elucidate the similarity of susceptibility phenotypes between the evolved strains, we computed Spearman correlation coefficients ($\rho$) for each pairwise comparison of their normalized susceptibility profiles (see STAR Methods). We detected 107 significant correlations ($\rho < 0.05$, a two-tailed significance test) between resistant strains. Interestingly, 67 (60%) pairwise comparisons had high positive correlation coefficients for strains resistant to drugs from different chemical classes suggesting convergent phenotypes (Figure S3A; Table S3). Among those strains were tetracycline- and macrolide- and quinolone-resistant strains. In contrast, 40 pairwise comparisons had a negative correlation between their susceptibility profiles ($\rho < 0.05$) suggesting orthogonal phenotypic states. Notably, negative correlations of susceptibility profiles were observed in 90% of cases between polymyxin- and β-lactam-resistant strains (Figure S3A). For instance, colistin- and ceftazidime-resistant strains had strong negatively correlated susceptibility ($\rho = −0.74$; $p < 0.0001$) (Figure S3A; Table S3). Interestingly, several strains resistant to β-lactams (aztreonam, carbenicillin, and ampicillin) also displayed reciprocal collateral sensitivity with colistin (Figure 1A).

To further examine the phenotypic states of the resistant strains, we reduced the dimensionality of the data using principal component analysis (PCA). This analysis revealed that resistant strains are divided into four groups that are positioned in different regions of PCA (Figure 2A), highlighting the convergence toward specific phenotypic states in response to antibiotic exposure. β-lactams, aminoglycoside, quinolone, and polymyxin antibiotics are commonly applied for the treatment of lung infections in CF patients. Notably, strains resistant to these antibiotic classes were positioned in different regions of PCA indicating that understanding the convergence toward drug-specific phenotypes for these drugs could inform treatment strategies. Interestingly, region II in the PCA plot included strains resistant to quinolones, macrolides, and tetracyclines (Figure 2A), highlighting that these different drug classes select for similar phenotypic states with strongly correlated susceptibility profiles ($\rho = 0.84 – 0.97$, $p < 0.0001$, Spearman correlation) (Figure S3A; Table S3).

**Adaptive Evolution of Clinical Isolates Leads to Collateral Sensitivity**

To explore further the phenotypic convergence in response to antibiotic exposure, we investigated whether antibiotic resistance evolution from different genetic starting points would lead to convergent evolution of their susceptibility profiles. We selected five clinical CF isolates from the DK2 clone type that share a common ancestor but have diverged during years of isolation in three different hosts (Marvig et al., 2013). We observed changes in susceptibility for all adapted clinical isolates, indicating that evolutionary trajectories toward collateral sensitivity can occur in divergent lineages (with diverse phenotypic and genotypic starting point) (Figure S3B). Importantly, several collateral sensitivity interactions remained preserved in the majority of strains tested (Figure S3C). For instance, resistance development for ciprofloxacin was consistently associated with collateral sensitivity toward aminoglycoside antibiotics in all different genetic backgrounds. In addition, the fold change relative to the ancestral strains was higher in clinical isolates than observed in PAO1 evolution. Notably, the clinical isolates evolved to azithromycin and ciprofloxacin resistance (173-1991-CIP and 173-1991-AZY) were 32-fold more sensitive to colistin antibiotics then the WT (Figure S3C; Table S1). Profound collateral sensitivity was also previously observed for *E. coli* clinical isolates (Iamov and Sommer, 2013), indicating the potential for exploiting collateral sensitivity to optimize antibiotic regimens.

**Resistance Evolution of Clinical Isolates Converges to Conserved Collateral States**

To explore the link between the phenotypic changes of laboratoy-evolved resistant PAO1 and clinical isolates, we determined the Spearman correlation coefficients for their resistance profiles. Overall, this analysis shows that exposure of different *P. aeruginosa* strains to a particular drug tends to increase the correlation between them (Figure 2B; Table S4). When considering selective antibiotic pressure in clinical isolates, all clinical isolates exposed to aztreonam and ciprofloxacin as well as 80% of azithromycin- and tobramycin-resistant DK2 strains increased the correlation of their susceptibility profiles to the respective antibiotic-resistant PAO1 strains (Figure 2B). For instance, the correlation coefficient for clinical isolate 173 evolved to ciprofloxacin changed from a negative $\rho = −0.67$ (p < 0.01) to a positive $p = 0.65$ ($p < 0.01$) (Table S4). The exception was the colistin-resistant strain, for which no changes in correlation $p$ were linked to the colistin-resistant PAO1 strain, indicating that the difference with PAO1 might be reflected in the different genetic background between DK2 and PAO1 (Gutu et al., 2015). Using PCA we observed that the phenotypic states of the ciprofloxacin and aztreonam evolved clinical isolates shifted their corresponding resistant PAO1 strain in response to antibiotic resistance evolution (Figures 2C and 2D). Indeed, this analysis indicates that for some antibiotics, exposure and subsequent resistance evolution leads to convergence toward specific phenotypic states in diverse phenotypic and genotypic backgrounds.

**Genetic Determinants Involved in Collateral Sensitivity and Resistance**

To explore the genetic basis of phenotypic changes in susceptibility profiles, we sequenced the genomes of experimentally evolved strains. We observed that the impact of drug exposure on genome-wide evolutionary paths causing collateral resistance and sensitivity were associated with drug resistance genes also found to be undergoing selection in chronically infected CF patients (Marvig et al., 2013). Mutations in seven out of nine pathoadaptive, antibiotic resistance genes (fusA1, ampC, ampD, gyrA, gyrB, mexB, and pmrB) were observed in our adaptive evolution experiment (Figure S4A; Table S5). Uniformly, PAO1 strains resistant to quinolone, macrolide, and tetracyclines had mutations in the pathoadaptive gene *nfxB* (Marvig et al., 2015a, 2015b) (Figure S4A). *nfxB* is a negative transcriptional regulator of MexCD-OprJ efflux (Poole et al., 1996). In addition,
as observed for resistant PAO1 strains, we detected nfxB mutations in all five ciprofloxacin-resistant DK2 lineages and three out of five azithromycin-exposed lineages (Table S5).

To test whether nfxB mutations were indeed associated with collateral sensitivity and resistance, thereby leading to a selective disadvantage during exposure to particular drugs such as amikacin or minocycline, we conducted a competition experiment between the PAO1 WT strain and a nfxB119C > T mutant (azithromycin evolved PAO1). We evaluated the frequency of the nfxB mutation from each mix population exposed to amikacin and minocycline drugs for which the nfxB 119C > T mutant was collaterally sensitive or collaterally resistant, respectively.

From these experiments, we observed that the strain carrying the nfxB mutation was selected against when treated with the collateral sensitivity drug amikacin (Figure 3A). As expected, the selective survival the nfxB 119C > T mutant was observed when the strains were exposed to the collateral resistance drug azithromycin (Figure 3B).

To further study the mechanisms associated with nfxB-induced collateral sensitivity, we conducted a proteomic characterization of the resistant strains evolved to azithromycin and ciprofloxacin resistance that harbored nfxB mutations. The MexC transporter protein, was the most upregulated protein in both strains (t ratio 4.2 for ciprofloxacin-resistant and 6.2 for...
detected for the azithromycin-exposed strains (Table S5). The increased abundance of the MexC protein suggested that the manipulation of drug efflux transporters could provide improved treatment effects by enhancing selective bacterial vulnerabilities. Importantly, nfxB is the only known regulator of MexCD-OprJ efflux (Poole et al., 1996) and mutations that lead to a truncated, incomplete, and non-functional NfxB protein would affect the repressor binding capacities (Figures S4C and S4D) suggesting that nfxB gene mutations could be a potential sequence-based biomarker indicating collateral sensitivity.

**nfxB Mutations Accumulate Late during Resistance Evolution**

A stepwise acquisition of the mutations that confer low-level resistance can lead to increased resistance to antibiotics (Solè et al., 2015) and, consequently, poorer treatment outcomes (Falagas et al., 2012). However, if such mutations also lead to collateral sensitivity, it may be possible to select against such resistance evolution through rational drug treatment. To assess this, ciprofloxacin- and azithromycin-treated populations were monitored for the presence of nfxB mutations at day 3, 6, and 8 during the adaptive evolution experiment. Day 8 was chosen because the treated populations reached maximal levels of resistance (Figure S1D). The first mutation detected in the ciprofloxacin-treated population was at day 6 in gyrA (248C > T) at a frequency of 12%, while no mutations were detected in nfxB (Figure 3D). Finally, at day 8, the gyrA mutation was present in 99.2% of the population, and three different nfxB were detected in the population at similar frequencies (Figure 3D). In populations exposed to azithromycin, four different mutations emerged, of which the mutation nfxB115A > C was detected in half of the total population at day 8 (Figure 3E). No other mutations were detected for the azithromycin-exposed strains (Table S5).

The tendency to fix nfxB mutations in populations at later stages of the adaptive evolution of ciprofloxacin resistance (after gyrA mutation) (Figure 3D) could suggest that strains harboring only a mutation in gyrA have the potential to acquire further mutations and change strain susceptibility profiles. To establish the association of collateral sensitivity with the nfxB mutations that emerged at the end of the adaptive process, we compared the PAO1 observations with selected the clinical isolate (173-2005), that emerged at the end of the adaptive process, we compared the PAO1 observations with selected the clinical isolate (173-2005) (Figure 4A). Interestingly, the 173-2005 isolate, which was previously determined to be the closest common ancestor of the DK2 lineage (Yang et al., 2011). For each longitudinal isolate, we determined changes in susceptibility profiles toward 22 drugs relative to the ancestral strain (30-1979) (Figure 4A; Table S1). In agreement with our hypothesis, we observed oscillatory dynamics in the resistance levels of isolates from patients across the decades of the longitudinal sampling. Indeed, the last longitudinal isolate analyzed for patient 333 exhibited increased susceptibility toward 14 drugs relative to the first isolate taken more than 15 years earlier (Figure 4A). Decreases in MICs were also observed for several antibiotics from the aminoglycoside, quinolone, and tetracycline drug classes in the two strains isolated in sub-lineage A (173-1991) and sub-lineage C (173-2005) (Figure 4A). Interestingly, the 173-1991 and 173-2005 isolates were the last isolates detected from each sub-lineage, suggesting that this reduction in MIC could be linked to their eradication.

**Phenotypic Convergence of Laboratory-Evolved Strains and Clinical Isolates**

To investigate potential associations between susceptibility profiles in the laboratory-evolved strains and clinical isolates,
we calculated the Spearman correlation coefficients between their susceptibility dynamics of the clinical isolates and the collateral sensitivity and resistance profiles of the laboratory-evolved strains (Figure 4A). A Spearman covariance matrix revealed 38 significant correlations between clinical isolates and one or more of the resistant PAO1 strains ($p < 0.05$, a two-tailed significance test) (Figure 4B; Table S6). Notably, several clinical isolates with high positive correlation coefficients to resistant PAO1 strains exhibited increased susceptibility toward different antibiotic classes. Such changes in resistance dynamics were particularly pronounced for the last isolate from patient 333 (333-2007c). This strain had increased sensitivity toward drugs from the quinolone, β-lactam, fosfomycin, and rifampicin drug classes (Figure 4A) and had a strong positive correlation to the colistin-resistant PAO1 strain ($p = 0.6; p < 0.01$) (Figure 4B; Table S6). In addition, negative correlation between clinical isolates and one or more of the resistant PAO1 strains ($p < 0.05$) was also observed (Figure 4B). Between PAO1-resistant strains strong negative correlation coefficients were observed for antibiotics that had reciprocal collateral sensitivities (e.g., colistin and aztreonam) (Figure S3A) indicating incompatible drug resistance pathways.

**Figure 4. Oscillatory Dynamics in Susceptibility Profiles from *P. aeruginosa* Chronically Infected CF Patients**

(A) Susceptibility profiles for clinical isolates obtained by longitudinal sampling of DK2 clinical isolates from three CF patients chronically infected by *P. aeruginosa*. For each strain, MIC values were determined toward 22 drugs. Drug susceptibility was determined based on the average values of five replicates. MIC values were normalized to the baseline susceptibilities of the immediate common ancestor of the DK2 isolates (isolate 30-1979) (Table S1).  

(B) A heatmap of Spearman’s correlation coefficients ($r$) summarizes the pairwise correlative relationship between the altered susceptibilities of the experimentally evolved resistant PAO1 strains and DK2 isolates from CF patients. The upper-right color panel is an indicator of the Spearman correlation coefficient ($r$). Circle size represents the strength of $r$. Only statistically significant correlations are shown ($p > 0.05$, two-tailed test) (Table S6).

**Phenotypic Convergence during Antibiotic Therapy In Vivo**

To assess whether collateral sensitivity might modulate population dynamics of a chronic *P. aeruginosa* population in the CF lung, we studied a chronically infected CF patient during a 2-week course of intensive antibiotic treatment. We performed a comprehensive phenotypic screen of 626 clinical isolates from sputum samples of a CF patient before (t1), during (t2), and at the end of intensive antibiotic therapy (t3) (see STAR Methods). Notably, the number of colonies that could be cultivated from the sputum sample t3 was significantly reduced compared to t1 and t2 ($p < 0.01$, one-way ANOVA) (Figure 5A), indicating effective antibiotic therapy for chronic CF lung infection. For all isolates recovered, we examined their phenotypic diversity based on antibiotic susceptibility for six antibiotics from the quinolone, β-lactam, aminoglycoside, and polymyxin classes (Figures 5B–5E; Table S7). The population before treatment (t1) exhibited the highest phenotypic diversity with regards to antibiotic susceptibility, which decreased significantly during the course of antibiotic treatment by 7-fold ($p$ value = 6.125e$^{-12}$, pairwise comparison of Euclidian distance using t test) (Figure 5B). Interestingly, the 275 isolates from the diverse population selected before intensive antibiotic treatment (t1) comprised...
both strains susceptible and strains resistant to all six antibiotics tested (according to EUCAST clinical breakpoints) (Figures 5C and S5A–SSF). For instance, different levels of colistin resistance were detected before treatment (e.g., isolates that were both 4-fold above and 7-fold below EUCAST clinical breakpoints for colistin were detected) (Figures 5C and S5A–SSF). Yet, all isolates from the end of antibiotic treatment (t3) exhibited MIC 4-fold below EUCAST clinical breakpoints for colistin (Figures 5E and S5A). Of note, collateral sensitivity toward colistin in laboratory evolution experiment was a consequence of resistance development to β-lactam and aminoglycoside antibiotics (Figure 1A), all of which were applied in the treatment of the studied CF patient. The observed selection for isolates susceptible to colistin suggest that this collateral sensitivity interaction is relevant when treating chronic lung infections in CF patients.

Since the laboratory evolved strains converged toward specific phenotypic states (Figure 2A), we also applied PCA to characterize the phenotypic convergence of P. aeruginosa populations during in vivo treatment. Interestingly, we observed a striking phenotypic convergence of the characterized isolates during treatment (Figures 5F–5H and S5G). While isolates obtained before the intensive treatment were found in all four regions (I–IV) of the PCA plot (Figures 5F and S5H), the isolates at the end of the treatment converged to one region of PCA plot (region II) (Figure 5H) that represented a phenotypically uniform population highly susceptible to colistin (Figures 5E and S5A).

**Antibiotic Therapy Selects for Genetically Distinct Subpopulations with Specific Phenotypes**

Based on the observation that antibiotic treatment converges a phenotypically diverse population to a uniform antibiotic susceptibility phenotype (Figures 5F–5H), we decided to genetically characterize these populations. The majority of isolates sampled at t1 clustered in two subpopulations that were characterized by different levels of susceptibilities to fluoroquinolone antibiotics (Figure 5C). Accordingly, we separated the t1 population into quinolone susceptible (t1-a) and quinolone-resistant isolates (t1-b) based on the EUCAST breakpoints (Table 1). Given that both populations t1-b and t3 were characterized by a high level of quinolone resistance, we were interested whether population t3 was related to the quinolone-resistant subpopulation t1-b. We compared individual and shared mutations detected (Table S8) among different populations and found that 92.3% of the SNPs detected in population t3 were also observed in subpopulation t1-b (Figure 6A; Table S9). This finding suggested that population t3 and a subset of t1-b population originate from the same lineage. On the other hand, only 10 SNPs detected in t3 population were shared with quinolone susceptible populations t1-a and t2. Notably, both populations (t1-a and t2) that were more susceptible to quinolone drugs shared 98.6% of mutations (Figure 6A; Tables S8 and S9), which suggests that these populations originated from the same lineage. Emergence of the quinolone-resistant t3 population descendant from a small subset t1-b was observed after drug treatment was switched from ceftazidime to levofloxacin (Figures 5C–5E). The phylogeographic relatedness between the different populations determined by population sequencing was also supported by whole-genome sequencing of nine individual isolates selected from different subpopulations (Figure 6B; Table S8). We observed that isolates from t1-b-A and t3-J populations were DK2 type, while single isolates from t1-a and t2 were different clone type (Marvig et al., 2015a).

**Selection against nfxB Mutants during Antibiotic Treatment in the CF Lung**

Our in vitro work demonstrated that nfxB mutations lead to an overexpression of the MexC transporter (Figure 3C) leading to collateral sensitivity toward aminoglycosides, β-lactams, and colistin (Figure 1A). We showed that nfxB 119C > T mutants where outcompeted by WT during exposure to the aminoglycoside amikacin. Accordingly, we speculated that nfxB mutations present in the t1 population might also be eradicated during the intensive antibiotic therapy in the studied CF patient. Accordingly, we mapped the reads from population sequencing data from t1-a and t1-b to the nfxB gene to identify putative collateral sensitivity mutations. We found that 37.3% of t1-b subpopulation harbored a mutation in the nfxB gene (nfxB245G > T) (Figure 6C). Although the t1-b subpopulation had overlapping phenotypic and genotypic similarities with the population that emerged at the end of treatment (t3), none of the isolates in populations obtained at t1-a, during (t2), or at the end (t3) of antibiotic treatment harbored mutations in nfxB gene (Figure 6D). Loss of isolates with nfxB mutations followed after exposure to β-lactam and aminoglycoside antibiotics toward which resistant PAO1 and DK2 strains harboring nfxB mutations were collateral sensitive (Figures 1A and S4A). This observation suggests that the nfxB245G > T mutation is conferring collateral sensitivity in vivo in a similar manner as observed in lab evolved strains. Furthermore, this finding supports the notion that treatment of chronically infected CF patients could be individualized based on specific diagnostic markers that are associated with a collateral sensitivity to specific drugs.

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**Figure 5. Shift in Susceptibility Profiles during Intensive Antibiotic Treatment In Vivo**

(A) Recovery of P. aeruginosa from sputum on selective media. Plating was done in five replicates for samples t1 and t2. For sample t3, 12 agar plates were used to recover P. aeruginosa. The line dots represent the average and error bars 95% CI.

(B) Decrease in overall phenotypic diversity during the course of antibiotic treatment. Change in phenotypic diversity was calculated based on Euclidian distance between the normalized values for susceptibility profiles.

(C–E) Sensitivity profiles during antibiotic treatment of CF patient. Heatmap represents quantification of the drug response for single isolates obtained before (C), during (D), and at the end of treatment (E). Antibiotic and class abbreviations are listed in Table 1. Color coding represents the fold above (yellow) or below (blue) the isolate MIC value relative to the EUCAST clinical breakpoints (Table 1). Drug susceptibility was determined based on the average values of five replicates (Table S7). The order of isolates was determined by hierarchical clustering using the similarity of normalized MIC values as the distance measure.

(F–H) Space plot of two principal component axes obtained from the 626 clinical isolates normalized susceptibility data for the EUCAST resistance breakpoints. Color coding depicts the sampling time points before (F), during (G), and at the end of (H) treatment. See also Figure S9.
DISCUSSION

Chronic lung infections caused by P. aeruginosa are challenging to treat due to the ability of this opportunistic pathogen to persist and develop resistance during treatment (Poole, 2011). In this study, we show that evolution of resistance was associated with up to 8- and 32-fold reductions in MICs toward other antibiotics for PAO1 and DK2, respectively. This level of collateral sensitivity could have substantial clinical impact for the management of chronic infections, in which patients are exposed to several rounds of antibiotics, or even lifelong antibiotic therapies, as is the case for CF patients (Johansen et al., 2004). Overall low MIC values within the susceptibility range are associated with better treatment outcomes and lower mortality rates (Falagas et al., 2012). For instance, a study on the impact of carbapenem MIC values on hospital mortalities revealed that for each 2-fold increase in the MIC value, the probability of death increased by 2-fold (Esterly et al., 2012). Accordingly, our findings indicate that treatment of chronic infections can be optimized through the rational deployment of drugs based on their collateral sensitivity and convergence toward distinct phenotypic states. For instance, our results suggest that application of ciprofloxacin results in subsequent resistance development and phenotypic convergence. Ciprofloxacin resistance could enhance the action of tobramycin, since the collateral sensitivity was observed in the resistant PAO1 and DK2 strains. Similarly, colistin action could be enhanced in bacteria that developed resistance toward ciprofloxacin or aztreonam. Collateral sensitivity observed toward colistin, an important drug for treatment of P. aeruginosa infections, additionally supports exploitation of collateral sensitivity to counter drug resistance.

Interestingly, we find that collateral sensitivity can evolve in response to exposure to drugs for which the organism is already resistant. This finding should be considered given the frequent polymicrobial infection of the CF airways. Indeed, P. aeruginosa may be exposed to drugs administered to target other organisms, such as S. aureus. We show that exposure to several chemical classes of drugs, used in CF patient therapy (tetracycline or macrolide) for other species than P. aeruginosa.
(Gibson et al., 2003), can modulate collateral sensitivity and resistance in \( P. \) \( \text{aeruginosa} \). Indeed, we observed phenotypic convergences toward collateral states for DK2 strains treated with antibiotics regardless of initial resistance level. Thus, we hypothesize that by using commonly applied antibiotics according to a specific schedule, even highly resistant strains could be sensitized to enhance the treatment efficacy.

The genetic changes that are selected for during chronic infections by \( P. \) \( \text{aeruginosa} \) of the CF airways are being elucidated through recent clinical genome sequencing projects that have led to the identification of pathoadaptive genes (Marvig et al., 2013, 2015a, 2015b). Notably, there is a substantial overlap between the pathoadaptive genes that have been identified in longitudinal clinical sequencing studies and in our studies, suggesting that some pathoadaptive mutations are linked to collateral sensitivity. For instance, mutations in the \( nfxB \) that confers resistance to the quinolones, are frequently encountered in clinical isolates (Marvig et al., 2015a, 2015b). We find that \( nfxB \) mutations are associated with collateral sensitivity driven by resistance evolution to several different drug classes and phenotypic convergence. \( nfxB \) mutants were eradicated from the lung of a chronically infected CF patient during treatment with aminoglycoside and beta-lactam drugs leading to the eradication of a quinolone-resistant subpopulation. These findings indicate that antibiotic treatment of chronic infections can be optimized by targeting specific mutations associated with collateral sensitivities and converged phenotypic states. Accordingly, we speculate that \( nfxB \) gene mutations or MexC protein abundance could be monitored in the clinic and potentially serve as a genomic or proteomic biomarker for collateral sensitivity.

Based on the analysis from in vivo evolved population, it seems likely that antibiotics could be grouped for cycling approaches to improve treatment success in chronic infections. Such treatment could be applied jointly to enhance the drug effect against susceptible isolates for treatment of infection against heterogeneous populations observed in chronically infected patients (Foweraker et al., 2009). Besides reducing the bacterial load, we also observed that such treatment lead to convergence to less heterogeneous populations with more uniform phenotype. We observed that, at the end of treatment, population was uniformly susceptible to colistin. This indicated that tailored treatment based on preserved sensitivity interactions could benefit infection management in treatment of CF patient infections and potentially lead to more complete eradication of the infecting population. Such treatment could be individualized based on specific genomic or proteomic biomarkers such as \( nfxB \) or MexC, which we have found to be linked to collateral sensitivity phenotypes. Future studies will likely identify additional genetic markers of collateral sensitivities, enabling improved and personalized treatment of chronically infected patients.

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Supplemental Information includes five figures and nine tables and can be found with this article online at https://doi.org/10.1016/j.cell.2017.12.012.

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**AUTHOR CONTRIBUTIONS**


**DECLARATION OF INTERESTS**

The authors declare no competing interests.

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**REFERENCES**


# STAR Methods

## Key Resources Table

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CONTACT FOR REAGENT AND RESOURCE SHARING

Further information and requests for reagents may be directed to and will be fulfilled by the Lead Contact, Morten Otto Alexander Sommer (msom@bio.dtu.dk).

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Bacterial Strains and Growth Conditions
All experiments were performed in MHBII medium or Synthetic CF sputum (Palmer et al., 2007) supplemented with 5% mucin (Wong et al., 2012). PAO1 and DK2 drug-resistant phenotypes were selected as described below. Clinical isolates of the \textit{P. aeruginosa} DK2 lineage were obtained from the Danish CF collection from patients 173, 211 and 333 (Marvig et al., 2013). The bacterial strains are described in Table S1.

CF Patient
Patient CF124 was 52 years old male suffering from cystic fibrosis genetic disorder. Patient was chronically infected with \textit{P.aeruginosa} for 43 years at the collection date. Sputum sample was collected during routine diagnostic sampling from chronically infected CF patient. The local ethics committee at the Capital Region of Denmark Region Hovedstaden approved the use of the stored \textit{P. aeruginosa} isolates: registration number H-4-2015-FSP. Patient gave informed consent.

At home, patient was receiving 600 mg each day of ceftizadime via inhalation. Patient was received to hospital during the period of acute exacerbation. First sputum sample was taken then (sample t1) and patient was treated with ceftazidime (2g, twice daily), azithromycin (250 mg, oral, once daily), meropenem (2 g, intravenously, twice daily) and tobramycin (400 mg, intravenously, once daily). On the day 7 of treatment, second sputum sample was taken (sample t2), and then the treatment was changed from ceftazidime to levofloxacin, twice daily (commercially available as Quinsar). Administration of other antibiotics remained the same following 7 days, at which point the third sputum sample was obtained (t3).

\textit{P.aeruginosa} Isolation from Sputum Samples
Sputum samples were stored in 15%–20% glycerol at 80%. For each sampling point, 300 \textmu L of stored sputum sample was plated onto large agar plates (area) containing selective \textit{P.aeruginosa} media (\textit{Pseudomonas} Isolation Agar, Sigma). Agar plates were incubated for 2 days (42 ± 2 h) at 37 \degree C. Single colonies were selected, grown in MHBII and stored at –80 \degree C for further phenotypic and genotypic characterization.
Adaptive Evolution Experiments
A single colony was grown overnight in synthetic CF sputum supplemented mucin (SCFM) media. Eight microliters of overnight culture were then inoculated into 1 mL of SCFM media containing the 2-fold dilution of antibiotics listed in Table 1. Populations were grown on an orbital shaker (180 rpm) at 37 °C in 24-well plates. After 22 hours, 8 μL of culture from the well with the highest concentration of antibiotics and showing minimal growth (as measured by an optical density of OD 600 > 0.4) was transferred into 1 mL of fresh SCFM medium containing a 2-fold dilution of antibiotics. On day 8, the bacteria reached EUCAST levels of resistance. Thus, during day 9 and 10, antibiotic concentrations remained the same as on day 8. Final drug-treated cultures were frozen at −80 °C in 15% glycerol. The strains were then streaked on solid media (SCFM supplemented with 3.5% agar), and a single colony was selected, grown in liquid SCFM and stored at −80 °C for further phenotypic and genotypic characterization.

METHOD DETAILS

Drugs
Drug working solutions were made from solid stock (Table 1). All drugs solutions were sterilized with 0.22 μm filters and stored at −20 °C until use.

Collateral Susceptibility Profiles and MIC Determination
Drug-resistant strains were streaked on Mueller-Hinton Agar (MHA) (Sigma) and incubated at 37 °C. The duration of incubation was variable for different strains. All PAO1 strains were incubated overnight (18 ± 2 h), while DK2 strains were incubated for 2 days (42 ± 2 h) due to slower growth. A single colony was selected and grown in Mueller-Hinton Broth II (MHBII) (Sigma). After overnight incubation (for the PAO1 strains) and 2-day incubation (for the DK2 strains) at 37 °C and 180 rpm, bacterial cultures were used for MIC testing. Approximately 1x10^6 cells per well were incubated in 96-well plates. For each strain, 5 sets of experiments were performed to determine the drug susceptibility. The percentage of inhibition was calculated according to the following formula: 1 - [A_600 drug/A_600 untreated control]. The inhibitory concentration was defined as the lowest concentration of the drug that inhibited 90% of the growth of the strain tested (MIC) relative to the WTE.

Competition Experiments
Overnight cultures of WT and azithromycin-exposed PAO1 strain were inoculated 1:1 to approximately 5x10^5 cell/well into 96-well plates. Mixed cultures were treated with 2 μg.ml^{-1} amikacin or 4 μg.ml^{-1} minocycline in MHBII. Control samples were not treated with antibiotics. Samples were incubated at 37 °C for 18 h. All experiments were performed in triplicates. Specific strain abundance was calculated based on amplicon sequencing described below.

Amplicon sequencing
Three replicates done for each completion experiment were joined in one sample and genomic DNA of mixed population was prepared using the DNA Blood and Tissue Kit following manufacturer instructions (QIAGEN). Two μg of DNA was used as template for PCR reaction to amplify the nfxB region. PCR primers (2_mexD_nfxB-_up ACGCTGTTTCACCAGGGTAG and 2_morA_nfxB-lp AGCATCAACAGGACCAGCACA) were designed to amplify full nfxB gene (564 bp) and surrounding region (full length PCR product size = 3021 bp). Specific PCR product was selected on 1% agarose gel. Gel-purified PCR product was used as DNA template for library preparation using the NexteraXT kit (Illumina). Amplicon sequences of mixed populations were obtained on the MiSeq platform.

Whole-genome Sequencing
Genomic DNA was prepared using the DNA Blood and Tissue Kit following manufacturer instructions (QIAGEN). Libraries were prepared using the NexteraXT kit (Illumina) and TrueSeq Nano (Illumina). Genome sequences of resistant strains were obtained on the MiSeq platform with a coverage of > 50 fold.

Variant Detection
The sequences were trimmed to exclude low-quality reads and reads less than 75 bp. The remaining reads were then mapped against the P. aeruginosa PAO1 (GenBank Accession number NC_002516.2) or DK2 (GenBank Accession number CP003149) reference genomes using Genomic Workbench 9.0.1. (CLC Bio, QIAGEN). Parameters were as follows: mismatch gap 2, mismatch count 3, similarity fraction 0.9 and length fraction 0.5.

Mutation Detection in the Genomic Data
Point mutations or short InDels were identified based on Quality-based variant detection approaches implemented in Genomic Workbench 9.0.1. Single-nucleotide variant detection was carried out using a neighborhood quality standard algorithm with a minimum neighborhood quality score of 15, a maximum gap penalty of 2 and a minimum variant base of 10. The minimum variant frequency was set to 80%. For population sequencing, the minimum variant frequency was set to 10%. For each mutation detected in population, presence of mutation below 10% was verified by additional analysis allowing detection of known low frequency variant
(1%-10%). Mutation detected for populations from CF sputum sample was filtered based on 5% frequencies and minimum 10 reads coverage. Variants were filtered using an additional WT PAO1 sequenced strain. The background mutations for WT PAO1 are listed in Tables S5.

Sample Preparation for Proteomic Analysis
P. aeruginosa overnight cultures were diluted 1:100 in 10 mL of MHBII. After 10 h of incubation at 37 °C and 180 rpm, cells were collected by centrifugation, snap frozen on dry ice and stored at –80 °C. Cell preparation and proteomic analysis were performed as previously described (Bonde et al., 2016). First, 100 μL of urea (8 M, 75 mM NaCl, 50 mM Tris-HCl, pH 8.2) was added to the cell pellets. After this, two 3-mm zirconium oxide beads (Glen Mills, NJ, USA) were added, and the cells were disrupted using a Mixer Mill (MM 400 Retsch, Haan, Germany) for 2 min at 25 Hz. Following 30 min at 4°C, the cells were again subjected to 2 min in the mixer mill, after which an additional 100 μL of the urea solution was added. Following another cycle of 30 min at 4°C followed by 2 min at 25 Hz, the samples were centrifuged 10 min, and 100 μL of supernatant was collected and diluted with 400 μL of 25 mM ammonium bicarbonate. Samples were concentrated to 100 μL using a 3 kDa cutoff filter. Samples containing 100 μg of proteins in 50 μL of solution were used for digestion. Before adding 1 μg/sample trypsin, 5 μL of 100 mM DTT was added, and samples were kept at 37°C for 45 min. Subsequently, 10 μL of 100 mM iodoacetamide was added, and samples were kept in the dark for 45 min. Tryptic digestion was carried out for 8 h, after which 10 μL of 10% TFA was added, and samples were StageTipped using C18 (Empore, 3M, USA) according to a previously described procedure (Rappsilber et al., 2007).

NanoUPLC-MSE Acquisition
For Nanoscale LC analysis of the trypsin-digested samples, a nanoACQUITY system (Waters, USA) equipped with a Symmetry C18 5-μm, 180 μm × 20 mm precolumn and a nanoACQUITY BEH130 C18 1.7-μm, 75 μm × 250 mm analytical reversed-phase column (Waters, USA) was used. For each sample, 1 μg of protein was traped on the precolumn using mobile phase A, consisting of 0.1% formic acid in water with a flow rate of 8 μL min−1 for 4 min. Mobile phase B consisted of 0.1% formic acid in acetonitrile. A reversed-phase stepped gradient was used to separate peptides: i) from 6% to 14% acetonitrile in water over 28 min, ii) from 14% to 25% acetonitrile in water over 40 min, iii) from 25% to 38% acetonitrile in water over 15 min, iv) from 38% to 60% acetonitrile in water over 10 min, and v) from 60% to 99% acetonitrile in water over 20 min. Between each injection, a 30 min wash method was applied. Both methods used a constant column temperature of 35°C and a flow rate of 250 nL min−1.

The described gradient data were acquired using a Synapt G2 (Waters, Manchester, UK) Q-ToF instrument operated in positive mode using electrospray ionization with a NanoLock-spray source. Using the internal fluidics system of the mass spectrometer, leucine enkephalin was used as a lock mass. The lock mass channel was sampled every 60 s. For each injection, the mass spectrometer was operated in resolution mode, with continuum spectra being acquired. During acquisition, the mass spectrometer alternated between low- and high-energy modes using a scan time of 0.8 s for each mode over 50–2,000 Da. In the low-energy MS mode, data were collected at a constant collision energy of 4 eV. In the elevated-energy MS mode, the collision energy was increased from 15 to 40 eV.

Protein Identification
Protein identification and quantification were obtained using Progenesis QI for Proteomics version 2.0 and the P. aeruginosa UniProt proteome database (ID: UP 208964). Settings for the PLGS search engine were FDR 1%, tryptic peptides with one missed cleavage allowed, and carbamidomethylation of cysteine residues as fixed modification and oxidation of methionine residues as variable modification. For quantification, only unique peptides of the proteins of interest were used, enabling comparisons of protein abundance across the different samples (Bantschek et al., 2007).

QUANTIFICATION AND STATISTICAL ANALYSIS
The inhibitory concentration was defined as the lowest drug concentration that prevented 90% growth (MIC or IC90). The percentage of growth inhibition was calculated according to the following formula: 1 – [Adrug/Acontrol]. Data for the MICs are presented as the means of 5 independent replicates (±SD). Heatmaps showing susceptibility profiles and correlations were generated in Excel (14.6.1). Hierarchical clustering was performed using the similarity of normalized MIC values as the distance measured in R software using “gplots” and “ggdendro” packages. To measure the significance of the fold of increase in resistance between WTE and resistant strains we calculated growth inhibition of resistant strain toward 3 different antibiotics. Based on these results, we approximated the distribution of growth inhibition using the mean and standard deviation of the five replicates. We then generated 3,000 of simulations using the growth inhibition distributions. The concentration associated with 90% growth inhibition is then extracted for both WTE and resistant strain from the results simulated for each antibiotic. For the two vectors (strains) associated, we employed t test with alternative hypothesis “greater” to test the fold of increase between 1 and 10 with increasing factor of 0.5. The p value associated with each fold of increase was reported.

Networks connecting collateral sensitivity or resistance were explored and visualized using Cytoscape (3.1.0) (Shannon et al., 2003). To detect collateral sensitivity drug cycles, we have developed a software system using Python 2.7.2 that reads the drugs collateral sensitivity profiles into a dictionary data structure which links the drug with its corresponding collaterally sensitive drugs.
A cycle is found if the first drug deployed maps to a certain number of drugs that consequentially collaterally sensitive to each other and the first drug in the cycle is collaterally sensitive to the last one drug. To determine the correlations between the susceptibility profiles of resistant strains, the MIC values were normalized to the WTE and log2 transformed. A Spearman’s correlation was chosen due to improved handling of non-linear correlations. The packages “PerformanceAnalytics” and “corrr” in R software were used for analysis of correlation plots, covariance matrix. The packages “FactoMineR,” “factoextra” were used for PCA analysis. The ggplot2 plotting system was used for data visualization.

Protein identification and quantification were obtained using Progenesis QI for Proteomics versions 2.0 with only unique peptides of the proteins of interest. To obtain a uniform normalization across all samples from different batches, 47 ribosomal proteins detected in each dataset were used to introduce the data normalization factors. Data are presented as the means of 3 independent replicas with the SE of difference. The abundance of specific proteins was calculated based on the levels of the proteins in the WTE samples. t tests were performed using PRISM 7.0a to determine the ratio of the proteins with significantly altered abundance (95% confidence). Only proteins with at least a 1.5-fold change relative to the WTE strains (p > 0.05, t test) and with 3 identified unique peptides were reported as the altered proteome in Figure S4B.

Phenotypic population diversity was calculated for each pair of isolates in the population. For this purpose, the Euclidian distance between the normalized value for susceptibility profiles of 6 antibiotics was calculated. This procedure formed a vector that includes all the pairwise distances between isolates in the population. The confidence level was determined using t test at 95% confidence level of the two vectors considering the alternative = “greater.” To specify the fold of increase, the diversity-declining population was multiplied by an increasing factor and compare with the diversity of population of interest.

**DATA AND SOFTWARE AVAILABILITY**

The collateral sensitivity drug cycle detection program is available at https://github.com/MostafaEllabaan/DrugCyclesPrediction/blob/master/DrugCycleDetector.py. All genome sequence data are available in Sequence Read Archive (SRA) under submission PRJNA414086. Raw proteomics data are available via ProteomeXchange with identifier PXD007972.
Figure S1. Selection for Resistance during Laboratory Evolution Experiments and Collateral Changes in Susceptibility Profiles, Related to Figure 1

(A–F) Increase in antibiotic resistance during adaptive evolution experiment in SCFM. Fold increase depicts the well from each day transfer was made in antibiotic gradient plate. Fold increase is calculated relative to the day 1.

(G–J) Resistance that alters the collateral sensitivity profiles of parallel evolved PAO1 strains. Three outcomes of resistance development were observed: (G) no change in susceptibility profiles relative to the WTE (black line), (H) collateral resistance or decrease in drug susceptibility relative to the WTE (red line) and (I) collateral sensitivity or increase in drug susceptibility relative to the WTE (blue line). For each strain, five replicates were performed to determine the drug susceptibility (±SD, error bars). (J) Significance test of the fold of difference in resistance between the WTE and ciprofloxacin resistant strain. Using the mean and standard deviation of the five replicates, growth inhibition of ciprofloxacin resistant strains toward three different antibiotics was calculated. P-value was determined using t-test test with alternative hypothesis “greater” for the fold increase between one and 10 (by factor 0.5).
Figure S2. Complex Networks of Interactions Based on the Collateral Susceptibility Profiles, Related to Figure 1

(A) Collateral sensitivity network. For collateral susceptibility networks, the directed path of each arrow represents the collateral sensitivity (blue) or collateral resistance (red) of an affected variable (drug-resistant strain) on the causal variable (drug). Antibiotic abbreviations are listed in Table 1.

(B) Number of collateral sensitivity cycles simulated for all drugs employed in the study. The cycles are based on PAO1 susceptibility profiles (Figure 1A).
**Figure S3. A Relationship between the Altered Susceptibilities of the Experimentally Evolved Resistant PAO1 and Collateral Sensitivity Profiles for DK2 Clinical Isolates, Related to Figure 2**

(A) A Spearman correlation matrix for all pairwise susceptibility profiles of PAO1 drug-resistant strains. MIC values were normalized to WTE strain and log_2 transformed. Upper right color panel is an indicator of the Spearman correlation coefficient ($r$). Circle size represents the strength of Spearman correlation's coefficient ($r$). Only statistically significant correlations are shown ($p > 0.05$, two-tailed test) (Table S3). Scatterplots represent a positive correlation between ciprofloxacin (CIP) and other strains resistant to four different chemical classes. The data displayed on the second scatterplot depict positive correlations (with aztreonam and two β-lactam resistant strains) and negative correlations (with aminoglycoside and polymyxin resistant strains). In addition, plots in yellow show strains for which no significant correlation was observed ($p > 0.05$, two-tailed test).

(B) Initial susceptibility levels for five DK2 isolates selected for the adaptive evolution experiment. Data are presented as the MIC fold change relative to the DK2 strain not exposed to antibiotics.

(C) Collateral sensitivity and resistance during adaptive evolution for DK2 drug resistant strains. The MIC values were normalized to the baseline susceptibilities of each WT for evolved DK2 isolates (WTE) (Table S1).
Drug class

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**Collateral resistance:** quinolones, macrolides, tetracyclines  
**Collateral sensitivity:** aminoglycosides, β-lactams, colistin

(legend on next page)
(A) Mutational events leading to drug resistance for PAO1 (Table S5). The order of the drugs and resistant strains was determined by hierarchical clustering using the shared mutation as a value for the distance measure. Antibiotic and class abbreviations are listed in Table 1.

(B) Changes in proteome in drug ciprofloxacin and azithromycin resistant strains harboring nfxB mutation. Fold change for specific proteins was calculated based on the level of the proteins in WTE sample. t test were preformed to determine the ratio of proteins with significantly altered abundance (95% confidence). Only proteins with at least 1.5-fold increase (P-value < 0.05, t test) were reported.

(C) MexCD-OprJ efflux is negatively regulated by NfxB repressor binding upstream of mexC gene.

(D) Mutation in nfxB lead affects repressor binding leading to expression of MexCD-OprJ efflux system. Expression of MexCD-OprJ efflux system resulted in increased abundance of MexC protein leading to collateral sensitivity and resistance.
Figure S5. Phenotypic Convergences for Heterogeneous *P. aeruginosa* Population during Antibiotic Treatment, Related to Figure 5

(A–F) Distribution plots for susceptibility profiles of clinical isolates toward six clinically relevant antibiotics.

(G) PCA plot for antibiotic susceptibility of clinical isolates obtained before (t1), during (t2) and at the end (t3) of intensive antibiotic treatment of CF patient.

(H) PCA plot for quinolone resistant strains before (t1-b) and at the end of intensive antibiotic treatment (t3) for CF patient. For all panels, normalized MIC values were used as data input. MIC or the inhibitory concentration was defined as the lowest concentration of the drug that inhibited 90% of the growth of the strain tested. For each strain, five replicates were performed to determine the drug susceptibility. All MIC data were normalized to EUCAST resistant breakpoint values and log₂ transformed.