Phenotypic bistability in *Escherichia coli*’s central carbon metabolism

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Abstract

Fluctuations in intracellular molecule abundance can lead to distinct, coexisting phenotypes in isogenic populations. Although metabolism continuously adapts to unpredictable environmental changes, and although bistability was found in certain substrate-uptake pathways, central carbon metabolism is thought to operate deterministically. Here, we combine experiment and theory to demonstrate that a clonal *Escherichia coli* population splits into two stochastically generated phenotypic subpopulations after glucose-gluconeogenic substrate shifts. Most cells refrain from growth, entering a dormant persister state that manifests as a lag phase in the population growth curve. The subpopulation-generating mechanism resides at the metabolic core, overarches the metabolic and transcriptional networks, and only allows the growth of cells initially achieving sufficiently high gluconeogenic flux. Thus, central metabolism does not ensure the gluconeogenic growth of individual cells, but uses a population-level adaptation resulting in responsive diversification upon nutrient changes.

Keywords bistability; flux sensing; metabolism; noise; persisters

Subject Categories Metabolism; Quantitative Biology & Dynamical Systems

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Introduction

Since the early studies of bacterial physiology, inoculation of a bacterial population into a new medium has been known to result in a period lacking apparent growth prior to growth on the new carbon source (Monod, 1949). This lag phase is classically attributed to the duration of the requisite biochemical adaptation processes in individual cells, which are thought to switch homogeneously and responsively to the new substrate (Fig 1A and B). However, biochemical processes are inherently stochastic and cause molecule abundances to fluctuate (Elowitz et al., 2002). These fluctuations are often suppressed, but can also be amplified and used to generate distinct phenotypes (Balaban et al., 2004; Ozbudak et al., 2004; Choi et al., 2008; Losick & Desplan, 2008). Experimental (Acar et al., 2008; Mitchell et al., 2009) and complementary theoretical studies (Russell & Leibler, 2005) have suggested that stochastically driven systems can prevail over deterministic designs in conferring population adaptability. Although metabolism continuously adapts to unpredictable environmental changes, and certain substrate-uptake pathways have been found to exhibit phenotypic bistability (Ozbudak et al., 2004; Acar et al., 2005), central carbon metabolism as a whole is thought to operate deterministically. The possible emergence of multiple coexisting phenotypes within an isogenic cell population provides an alternative, but untested, hypothesis that the apparent lag time is caused by the exclusive growth of an initially small phenotypic subpopulation (Fig 1C).

The phenotypic subpopulation could be generated in two ways. First, the cells could ‘anticipate’ the environmental change by stochastically switching phenotype at any time. In this case, adaptation to a new carbon source is a passive process accomplished by cells that switched phenotype prior to the environmental change (Russell & Leibler, 2005; Acar et al., 2008) (Fig 1D), similar to the mechanism employed by type II persister cells (Balaban et al., 2004). Second, an initially homogeneous population could actively respond to the environmental change with phenotype diversification. In this case, only a stochastically generated subpopulation of cells adapts to growth under the new conditions (Fig 1E). This responsive diversification resembles the mechanism of type I persister cells, which acquire antibiotic tolerance in response to an environmental trigger (Balaban et al., 2004).

Using *Escherichia coli* as a model system, we set out to determine which of these adaptation strategies (the homogeneous strategy of responsive switching, or either of the two heterogeneous strategies, responsive diversification or stochastic switching) is used when changing environmental conditions require gluconeogenic, rather than glycolytic, growth. At the molecular level, this adaptation requires a major reorganization of central carbon flow, which *E. coli* accomplishes by repressing glycolytic genes and inducing gluconeogenic genes (Kao et al., 2005), particularly those participating in gluconeogenic reactions (pckA, maeB, sfoA), the Embden-Meyerhoff pathway (Keseler et al., 2009) and, in the case of acetate growth, the acetate uptake pathway (ack, pta) and glyoxylate shunt (aceBAK) (Wolfe, 2005).

Here, combining experiment and theory, we show that an isogenic, homogeneous *Escherichia coli* population, upon a shift...
Results

Growing and non-growing phenotypes are present after a carbon source shift

To determine whether the adaptation of *E. coli*’s central metabolism from glycolytic to gluconeogenic growth involves one or two phenotypes, we conducted substrate shift experiments from glucose to the gluconeogenic substrates acetate, fumarate, malate and succinate (Fig 2A). Just before the substrate shift, we stained the cellular membranes with a fluorescent, membrane-intercalating dye. Because each cell’s fluorescence intensity is halved with every cell division (see Supplementary Materials and Methods), this assay reports on individual cell’s growth history in the new environment. We determined the distribution of fluorescence intensity in a population at multiple time points following substrate shifts (Fig 2B).

Two cellular subpopulations emerged following exposure to each tested gluconeogenic substrate; the cells of one subpopulation retained high fluorescence, because they did not divide, and cells of the other subpopulation increased in number at the same rate as their fluorescence declined, indicating growth (Fig 2B and C). We quantified the fraction of cells that managed to adapt to gluconeogenic growth (α) as well as the steady-state growth rate of the growing cells (μg) by fitting a model of two Gaussian distributions and of exponential growth for the growing population to the total-population fluorescence intensity distribution at multiple time points (see Supplementary Materials and Methods). For all tested substrates, at a concentration of 2 g l⁻¹, surprisingly, small fractions of cells adapted to gluconeogenic growth (αAcetate = 0.5 ± 0.04, αFumarate = 0.001 ± 3 × 10⁻³, αMalate = 0.049 ± 0.013, αSuccinate = 0.017 ± 0.005; Supplementary Fig S1).

We excluded spontaneous suppressor mutations as a possible cause of the diversification; when cells derived from the growing subpopulation were streaked on a Luria Bertani medium plate, and single colonies were used to repeat the experiment (see Fig 2A), again two distinct growth phenotypes emerged with an identical growing population fraction α. Also, we excluded dye toxicity as potential alternative explanation (Supplementary Fig S2A) and confirmed that the non-growing cells remain viable after carbon source shift; after transferring a glucose-adapted population to 2 g l⁻¹ fumarate, where only 0.1% of the cells resumed growth, we determined at multiple time points the number of viable cells by dilution plating and the total cell count using flow cytometry. At all time points, we found that the number of viable cells was equivalent to the total cell count (Supplementary Fig S3A and B). Also non-growing cells resumed growth on glucose (Supplementary Fig S3C–G).
To discriminate between the two possible heterogeneous adaptation strategies (Fig 1D and E), we investigated whether the two phenotypes were generated at the time of the shift in carbon source (responsive diversification), or whether a phenotypic subpopulation adapted to gluconeogenic growth already existed in the glucose phase prior to the shift in carbon source (stochastic switching).

We grew E. coli on glucose with $^{13}$C-labeled acetate and measured $^{13}$C-enrichment patterns in the protein-bound amino acids. The mass distribution vectors of the amino acids revealed a natural labeling pattern for seven amino acids and $^{13}$C-enriched labeling pattern for eight amino acids (Supplementary Fig S4A). Mapping the amino acids to their respective precursor metabolites in central carbon metabolism (Supplementary Fig S4B) indicated that $^{13}$C-enrichment occurs only in amino acids derived from metabolites occurring below pyruvate (i.e. from the tricarboxylic acid cycle), but not in those amino acids that are derived from glycolytic intermediates above pyruvate. Therefore, next to the excretion of acetate during the glucose phase (Fuhrer et al., 2005), acetate is simultaneously also taken up. However, the carbon derived from acetate is only cycled through the tricarboxylic acid cycle and does not enter the Embden-Meyerhoff pathway for gluconeogenesis. A phenotypic subpopulation growing on acetate would have to perform gluconeogenesis, and thus, glycolytic intermediates above pyruvate and the amino acids derived from them would contain $^{13}$C label. As no $^{13}$C label was found in these compounds, a stochastically generated, pre-adaptation subpopulation growing solely on acetate does not exist in the presence of glucose or—if obscured by the measurement uncertainty—is too small to account for the growing phenotype potentially. This result is consistent with carbon catabolite repression (Stulke & Hillen, 1999), but not with stochastic switching. Further, flow cytometry (Supplementary Fig S4C and D) uncovered no evidence of stochastic inter-phenotype switching on the gluconeogenic carbon source, indicating that the two phenotypes were stable. Thus, we concluded that two stable phenotypes were generated at the time of the carbon source shift through responsive diversification (Fig 1E).

Subpopulation proportions depend on the carbon uptake rate

Next, we investigated whether responsive diversification is dependent on the concentration of the carbon source. We first focused on acetate, which E. coli produces from excess glucose. We found that the concentration of acetate in the glucose culture before the carbon source shift did not affect $\alpha$ (Supplementary Fig S5), and thus, the presence of acetate before the shift does not prime the cells for later acetate consumption. However, the acetate concentration after the shift determined not only the cells’ growth rate $\mu_{\text{ac}}$ (with its acetate concentration-dependence following a hyperbolic Monod kinetics (Fig 3A) and kinetic parameters similar to previously published values (Wolfe, 2005)), but intriguingly also $\alpha$, the fraction of adapting cells, which increased hyperbolically with the acetate concentration and leveled off at approximately 0.6 (Fig 3B). The acetate concentration-dependency of the growth rate that we observed suggests that the extracellular acetate concentration apparently influences the acetate influx and therefore also the flux into central metabolism, which let us hypothesize that also the observed $\alpha$’s dependency on the acetate concentration might be tied to the rate of substrate uptake.

To verify that $\alpha$ is indeed influenced by the substrate-uptake flux, we turned to fumarate, which—in contrast to acetate—is actively...
A key regulator of the glycolysis/gluconeogenesis switch (Saier et al., 2008); it targets almost all genes involved in the Embden-Meyerhoff pathway, the citric acid cycle and aerobic respiration (Shimada et al., 2011). FBP is an intermediate in the central Embden-Meyerhoff pathway and may signal the metabolic flux derived from the diverse gluconeogenic carbon sources.

First, we tested whether the Cra-FBP system indeed constitutes a flux sensor as predicted (Kotte et al., 2010). We used reporter plasmids to measure Cra activity for multiple acetate concentrations and, thus, multiple acetate uptake rates. We detected a strong positive correlation between gluconeogenic flux and Cra activity (Fig 4A), consistent with the prediction that the concentration of FBP, which inhibits Cra, decreases with increasing gluconeogenic flux (Kotte et al., 2010).

Next, we asked whether Cra activity, the output of the Cra-FBP flux sensor, is decisive for generating responsive diversification. Increasing Cra activity prior to the substrate shift (by growing cells in different glucose-limited chemostat cultures) increased \( \alpha \) values (Fig 4B). We then perturbed Cra activity by individually perturbing the Cra and FBP levels. We expressed Cra using a plasmid with an IPTG-inducible promoter in a \( \text{cra}^{-} \) deletion mutant and found that \( \alpha \) was markedly reduced in the uninduced state (49 \pm 15 Cra copies) compared to the wild-type (72 \pm 21 Cra copies), but the growth rate of the growing population, \( \mu_{gl} \), was not affected. When induced with 10 \( \mu \text{M} \) IPTG (248 \pm 12 Cra copies), the wild-type \( \alpha \) was restored (Fig 4C). Toward lowering the FBP concentration, we overexpressed the FBP-consuming enzyme fructose-1,6-bisphosphatase (Fbp) using a plasmid. Because we expected an increase in \( \alpha \), we shifted the cells to 0.75 g l\(^{-1}\) acetate and found that \( \alpha \) indeed increased from the wild-type level of 0.25 \pm 0.04 up to 0.70 \pm 0.08 upon induction of the enzyme Fbp (Fig 4D). Toward increasing the FBP concentration in wild-type cells, we added 2-deoxyglucose-6-phosphate, a glucose-6-phosphate analogue that is not metabolized (Dietz & Heppel, 1971), but inhibits Fbp activity (see Supplementary Materials and Methods); we detected a notable decrease in \( \alpha \).
To help understand this rather complex system, we resorted to the descriptive power of a mathematical model. We thus constructed a differential equation model (see Supplementary Materials and Methods) that combines the reaction sequence from gluconeogenic substrate uptake to FBP formation into a single reaction catalyzed by a fictitious super-enzyme E. The production of E is activated by Cra (for the effect of more nuanced regulation, see Supplementary Materials and Methods), and the activity of Cra is inhibited by FBP. One way to make such a feedback loop positive is if FBP levels drop with increasing flux thereby introducing a second negative sign into the feedback loop (note, the first negative sign is introduced by the inhibition of Cra by FBP), such that the sign of the overall feedback loop becomes positive and the generation of two coexisting phenotypes possible. Through a metabolomics experiment, we verified that FBP levels indeed decrease with increasing gluconeogenic flux (Fig 5B).

Next, we investigated how the flux-FBP level relationship could be inverted. While we found that the Fbp expression levels are constant across the employed acetate concentrations (between 0.5 and 2 g l⁻¹ acetate; P-value 0.86), Fbp’s strong allosteric activator PEP (Hines et al., 2006; Link et al., 2013) showed higher concentrations at the higher flux conditions (Fig 5C) suggesting that this flux-dependent feed-forward activation of Fbp activity on the allosteric level could invert the flux-FBP level relationship. If strong enough, the flux-dependent allosteric feed-forward activation of Fbp’s activity by PEP turns the sign of the global Cra feedback loop positive
Figure 5. Model of the bistability-generating circuit.

A. Model of the bistability-generating circuit. E denotes a fictitious super-enzyme catalyzing combined reactions. The enzyme fructose-1,6-bisphosphatase (Fbp) is activated in a flux-dependent manner. The metabolite fructose-1,6-bisphosphate (FBP) represses E production by inhibiting E’s transcriptional activator Cra. PEP, phosphoenolpyruvate.

B, C. Population-averaged metabolite levels after a switch from glucose to acetate (0.5 g L−1, open symbols; 2 g L−1 closed symbols) showed that at the higher acetate concentration—and thus at the higher gluconeogenic flux condition—FBP levels are lower (B), while the level of the strong allosteric activator of the Fbp enzyme, phosphoenolpyruvate (PEP), is significantly higher at increased fluxes, accomplishing a flux-dependent feed-forward activation of the Fbp enzyme (C).

D. Bifurcation diagram of metabolic steady-state fluxes J as a function of the extracellular acetate concentration. The system is capable of expressing two stable steady-state fluxes (bold lines) and one unstable steady-state flux (dashed line), which acts as a watershed separating the convergence regions of the high (growing) and low (non-growing) stable steady states. Arrows show the direction of system dynamics.

Source data are available online for this figure.

and allows for the generation of two distinct phenotypes from a unimodal distribution. In the model, we included a cooperative flux-dependent activation of the enzyme Fbp (see Supplementary Materials and Methods).

The separation of a homogeneous population into two subpopulations is illustrated by a bifurcation analysis of the mathematical model performed in the bistable regime (see Supplementary Materials and Methods). Two stable metabolic fluxes emerge, which can be interpreted as the growing and non-growing phenotypes, and which are separated by a watershed in the bifurcation diagram (Fig 5D, Supplementary Fig S8). If, after a substrate shift, a particular cell immediately achieves a gluconeogenic flux above the watershed, the system dynamics drag it toward the high steady state and it adopts the growing phenotype; otherwise, it approaches the low steady state and adopts the non-growing phenotype. This system requires a capacity for immediate utilization of gluconeogenic substrates upon glucose removal, which was demonstrated by the 13C population tracer experiments (Supplementary Fig S4A and B). A unimodal population separates into these two coexisting phenotypes when cell-to-cell variation in the abundance of the super-enzyme E, which is encouraged by the very low copy number of Cra (see Fig 4C), causes E’s established flux to exceed the watershed in some cells but not in others. After separation, additional state-stabilizing regulatory adjustments likely occur in non-growing, and possibly growing, cells, but these are not covered by the model. Differences between the cells’ capability to generate flux to FBP after the carbon source shift effectively cause the bifurcation. Flux bottlenecks are likely generated by stochastic differences in gluconeogenic enzyme expression, with the bottlenecks eventually residing in each individual cell at different reactions.

The model’s system properties were consistent with our experimental observations. Increasing acetate concentrations in the range of the Monod constant and a greater abundance of the fumarate transporter resulted in higher gluconeogenic uptake fluxes, shifting cells above the watershed and increasing χ (Fig 3A–C). The carbon flux derived from all tested gluconeogenic substrates is funneled into the Embden-Meyerhoff pathway; therefore, the mechanism described in the model can explain responsive diversification for all tested substrates. Further, mathematical model analysis (see Supplementary Materials and Methods) predicted that a decrease in the production rate of E would increase the watershed level, which would substantially reduce χ but, counter-intuitively, only marginally affect μg, as the flux of the high steady state would basically remain unaltered (Fig 6A). One attempt to lower the ‘production rate’ of the fictitious super-enzyme E in a concrete experiment is to knock out isoenzymes (acrA, acrB) or parallel pathways (maeBsfCA, ppsA, pckA; Fig 6B) subsumed into E. Besides potentially introducing metabolic flux bottlenecks, these knockouts might also introduce bottlenecks in the ‘production rate’ of the fictitious super-enzyme E. Following the substrate shift, several of these mutants (ppsA, maeBsfCA, acrB) exhibited a marginally reduced μg and drastically reduced χ (Fig 6C), suggesting the introduction of a transcriptional but not metabolic bottleneck; wild-type-like values were restored when the alternative isoenzyme or parallel pathway was overexpressed (Supplementary Fig S9). Suppressor mutants were excluded in strains that showed the long lag phase (Supplementary Table S1).

Taken together, our experimental findings and the model-based integration of these findings in a system context strongly suggest that the molecular system shown in Fig 5A is the mechanism responsible for the generation of responsive diversification upon carbon source shifts.

Cells of the non-growing phenotype are dormant persisters

Lastly, we asked whether the non-growing dormant cells that occur after the carbon source shift resemble persisters cells tolerant to antibiotics. Persister cells are dormant variants of regular cells that can survive treatment with antibiotics, but remain sensitive to that antibiotic upon being regrown (Lewis, 2010). To test for our non-growing cells’ antibiotic tolerance, we subjected cells from several time points after a glucose-to-fumarate shift to different antibiotics for 2 h and determined cell viability by plating. Using antibiotics that kill growing cells, specifically ampicillin, kanamycin, and rifampicin, we found that 86 to 97% of the non-growing cells tolerated the treatment (Supplementary Fig S10A–D). Using antibiotics that also kill non-growing cells, specifically ofloxacin and mitomycin C, we detected that 18% of the non-growing cells tolerated treatment (Supplementary Fig S10E and F). Cells exponentially growing on glucose did not survive identical antibiotic treatment. We excluded that the tolerance exhibited by the non-growing cells was due to genetically acquired resistance; when cells that survived antibiotic
exposure were regrown on glucose minimal medium, renewed antibiotic exposure killed all of the cells. Thus, the cells of the non-growing phenotype, largely tolerant against antibiotics, resemble type I persister cells (Balaban et al., 2004), and here, we show that persister cells can arise from insufficient carbon uptake rates, for example, occurring after shifts in nutrient availability.

**Discussion**

Our data show that, upon a shift from glucose to various gluconeogenic carbon sources, an isogenic, homogeneous cell population responsively diversifies into growing and non-growing phenotypes, causing an apparent lag time in population-level growth. The responsible molecular mechanism resides at the core of central metabolism. Metabolic flux is used as a controlling factor, and a cell grows on gluconeogenic substrates only if it achieves a gluconeogenic flux above a crucial watershed. Non-growing cells neglect the offered carbon source and enter a protective dormant state in which they are, for example, tolerant to antibiotics and resume growing when glycolytic conditions return.

Responsive diversification offers explanation for the phenomenon of lag phases

Lag phases are well known characteristics of almost every bacterial cell culture and were traditionally attributed to the duration of necessary biochemical adaptation processes. However, this theory fails to explain long lag phases, and thus, these lag phases are often ascribed to spontaneous mutations (Egler et al., 2005; Takeno et al., 2010).

For the first time, we offer a consistent explanation for the phenomenon of lag phases. Although the time needed for biochemical adaptation may still contribute to lag phases, we showed that lag time is largely caused by the exclusive growth of an initially small subpopulation (see Supplementary Fig S7), and we found that this also generalizes to other carbon source shifts (see Supplementary Table S1). Colleagues from the Netherlands recently confirmed similar behavior in yeast (van Heerden et al., 2014) and L. lactis (Solopova et al., 2014). With knowledge of the respective diversification-generating mechanism, wild-type lag phases can be shortened, as we demonstrated for fumarate (Fig 3C) and acetate (Fig 4C and D) with broad implications for microbiology and biotechnology.
Flux-induced phenotypic bistability generalizes to central metabolism

Not being specific to a particular gluconeogenic substrate, the molecular mechanism that generates phenotypic bistability in response to a glucose-to-gluconeogenic substrate shift is general in nature and resides at the core of central metabolism. Thus, phenotypic bistability, which has so far only been observed in a few specific substrate-uptake pathways (Ozbudak et al, 2004; Acar et al, 2005), generalizes to central metabolism as a whole. Such bistable phenotypes ultimately arise from stochastic variability in biologic molecule abundance and are generated through positive feedback (Balazsi et al, 2011). A crucial element of the here uncovered feedback loop is the metabolic flux that connects carbon uptake to the level of an intracellular, flux-signaling metabolite (i.e. FBP). As the previously observed occurrences of bistability within substrate-uptake pathways (Ozbudak et al, 2004; Acar et al, 2005) also involve flux sensor motifs (Kotte et al, 2010), flux-induced bistability may be a ubiquitous principle of metabolism.

Responsive diversification manifests a trade-off of cellular regulation

Our study reveals that, after glucose depletion, surprisingly few cells accomplish the transition to gluconeogenic growth. In fact, as Fbp overexpression increases α in the wild type (Fig 4D), E. coli’s adaptation to gluconeogenic substrates is not optimal at the single-cell level. Why did such behavior evolve? Our results indicate that fast glycolytic growth correlates negatively with α (Fig 4B). Only cells that refrain from growing very fast on glucose maintain their ability to switch to gluconeogenic growth upon glucose depletion; cells with a very fast glycolytic growth rate cannot generate sufficiently high initial gluconeogenic flux through the Embden-Meyerhoff pathway and must enter dormancy. This observation indicates an inherent trade-off between the rate of glycolytic growth and the ability to adapt to gluconeogenic growth, which is in agreement with a recently suggested trade-off between optimality under one given condition and minimal adjustment between conditions (Schuetz et al, 2012).

Thus, our results demonstrate that E. coli’s adaptation to fluctuating carbon sources is not optimized at the single-cell level, but at the population level eventually through conditional bet-hedging (Veening et al, 2008; Beaumont et al, 2009; de Jong et al, 2011). Cells could already hedge their bets on glucose and balance their glycolytic growth rate with their ability to adapt to gluconeogenic growth. The population is unimodal on glucose, and each cell is placed stochastically and gradually in a landscape between these two competing objectives. Thus, the population could cope with the present trade-off by sampling a large space of possible expression patterns. The conditional bet-hedging becomes apparent only after glucose depletion, when a certain level of adaptability to gluconeogenic growth is suddenly needed; thus, responsive diversification is observed.

Limited carbon influx is a prime trigger of persistence

Finally, our data indicate that a threshold carbon uptake rate exists, below which rate cells enter dormancy and become largely tolerant to a number of antibiotics. Upon the cessation of glycolytic growth conditions, a flux-induced mechanism controls whether cells become dormant. This finding could explain why the frequency of persister cells increases during entry into the stationary phase (Gefen et al, 2008; Luidalepp et al, 2011). An intriguing question is whether the small population that occurs naturally and makes up the basis of persistence (Balaban et al, 2004; Schumacher et al, 2009) is also triggered by (stochastically) limited carbon uptake rates.

Materials and Methods

Strains and plasmids

Escherichia coli K12 strain BW25113 served as the wild-type strain. Gene deletions were transferred to the wild-type background from deletion strains of the Keio collection (Baba et al, 2006) using P1 phage transduction (Mitchell et al, 2009) and verified by colony PCR. The IPTG-inducible over-expression plasmids pPtac-cra, pPtac-acnA, pPtac-fbp as well as the reporter plasmid pPpykF-gfp were obtained from available libraries (Kitagawa et al, 2005; Saka et al, 2005; Zaslaver et al, 2006). The reporter plasmid pPgbp-gfp was constructed in analogy to the plasmids in the library by (Zaslaver et al, 2006). A de-regulated pykF reporter plasmid variant, pPpykF*-gfp, was constructed by mutating the Cra binding site via PCR. See Supplementary Materials and Methods for details on strains and plasmids.

Growth media

M9 medium with 1.5 g l⁻¹ (NH₄)₂SO₄, and 1 mg l⁻¹ thiamin-HCl as the sole vitamin, was used. Carbon sources were added from stock solutions adjusted to pH 7.

Cultivation

Pre-cultures from single colonies were grown overnight in M9 plus 5 g l⁻¹ glucose. Respectively required antibiotics were added to precultures with strains carrying plasmids (ampicillin, 20 μg ml⁻¹; kanamycin, 25 μg ml⁻¹). Cells were re-inoculated into M9 medium plus 5 g l⁻¹ glucose. For batch cultures, cells were cultivated in 500-ml Erlenmeyer flasks containing 50 ml growth medium (300 rpm, 37°C). For chemostat cultures, cells were grown in mini-chemostats as described by Nanchen et al (2006) on M9 medium plus 1 g l⁻¹ glucose.

Carbon source switching experiments and cell staining

A total of 1.5 × 10⁹ cells from an exponentially growing culture, or a chemostat culture, was harvested in mid-exponential phase (OD₆₀₀ ≈ 0.5) and centrifuged for 4 min at 4,000 g and 4°C. The supernatant was discarded, the cells washed or stained, and inoculated (~2 × 10⁷ cells ml⁻¹) into M9 medium plus acetate, succinate, fumarate, or malate. For washing, the cells were resuspended in 5 ml ice-cold M9 medium, centrifuged a second time, and resuspended in 1 ml of room temperature M9 medium. For staining, the cells were resuspended in 500 μl of room temperature dilution
buffer C (Sigma-Aldrich). A freshly prepared mixture of 10 µl PKH26 or PKH67 dye (Sigma-Aldrich) and 500 µl dilution of buffer C (both at room temperature) was added. After 3 min at room temperature, 4 ml ice-cold filtered M9 medium containing 1% (w/v) bovine serum albumin (AppliChem) was added. After centrifugation, the supernatant was discarded and the cells washed twice.

Flow cytometry

Samples were diluted with M9 medium to an OD_{600} of 0.001. Briefly, vortexed samples were analyzed with either a BD Accuri C6 flow cytometer (BD Biosciences; 20 µl, flow rate: medium, FSC-H threshold: 8000, SSC-H threshold: 500) or a FACS Calibur flow cytometer (BD Biosciences; 1 min, no gating, flow rate: high, FSC: E02, SSC: 327, FL-1: 999, FL-2: 700: all log, primary: SSC, threshold: 50), with gating performed in FlowJo 8.2 (Tree Star). To determine the absolute cell counts with the latter instrument, 20 µl of vortexed counting beads (CountBright, Invitrogen) was added to a 380 µl cell suspension prior to analysis.

$^{13}$C labeling experiment

To identify whether an acetate-growing phenotypic subpopulation already exists in the glucose growth phase, cells were grown in M9-glucose pre-culture, transferred to two M9-glucose (5 g l$^{-1}$) main cultures supplemented with either 1 g l$^{-1}$ unlabeled (i.e. naturally labeled) or 1 g l$^{-1}$ fully $^{13}$C-labeled acetate. Samples were taken in the mid-exponential growth phase ($OD_{600} = 1.2$) from culture with the labeled and unlabeled acetate, and a positive control sample was taken in the stationary phase ($OD_{600} = 3.3$) from the culture with the labeled acetate. At this point, the labeled acetate was taken up. Samples were processed according to (Ruhli et al, 2010) and labeling patterns in the protein-bound acids analyzed by GC-MS (Zamboni et al, 2009).

Fructose-bisphosphatase (Fbp) and Cra overexpression

The wild-type strain, the $f$bp deletion mutant, the $f$bp deletion mutant harboring the IPTG-inducible plasmid p$Ptac-fbp$, and the cra deletion mutant carrying the IPTG-inducible plasmid p$Ptac-cra$ were grown in M9 medium plus glucose (5 g l$^{-1}$) with 0 or 10 µM IPTG, then transferred to M9 medium plus fumarate (2 g l$^{-1}$) with 0, 1, 10, or 100 µM IPTG. Uptake rates at different IPTG levels were determined in fumarate-adapted cultures, where cell counts were determined at different time points by flow cytometry, and extracellular fumarate concentrations with HPLC. Dynamic cell counts and fumarate concentration data were fitted (MCMC toolbox for Matlab) to a model describing fumarate depletion and cell growth with the growth rate following Monod kinetics.

Quantification of Cra abundance

The wild-type and cra deletion mutant harboring the IPTG-inducible plasmid p$Ptac-cra$ were grown in M9 medium plus glucose (5 g l$^{-1}$) or M9 plus acetate (0.75 g l$^{-1}$) plus 0 or 10 µM IPTG. Harvested cells were washed and lysed, and the extracted proteins were digested with trypsin as described previously (Malmstrom et al, 2009). Then, 10 pmol of heavy labeled reference peptide was added to the digests, each containing 100 µg of total peptide. After desalting the peptides with macro-spin columns (Harvard Apparatus), an aliquot containing 1 µg of peptide was subjected to targeted mass spectrometry using previously specified instrument settings (Picotti et al, 2009). The total number of cells in the samples was determined by flow cytometry. Averages and standard deviations were derived from glucose experiments for the wild-type cells and from glucose and acetate experiments for other strains.

Quantification of Cra activity

Wild-type cells, wild-type cells harboring the p$PpykF$-gfp plasmid, and wild-type cells carrying the p$PpykF^*$-gfp plasmid (a variant with the Cra binding site removed) were adapted to a range of acetate concentrations, transferred to a plate reader (TECAN Infinite Pro 200), and grown at the steady state. Cra activity was calculated as 1 (promoter activity $pykF_{regulated}$/promoter activity $pykF_{deregulated}$) (Bintu et al, 2005). For batch cultures, promoter activities for the regulated and the deregulated $pykF$ promoter were calculated as dGFP/dt/OD during exponential growth. For chemostat cultures, promoter activities were calculated as $D \times GFP/OD$, where D denotes the dilution rate. Correction for background fluorescence for batch and chemostat cultures was performed using a strain bearing a promoterless GFP reporter plasmid.

Quantification of FBP and PEP levels

Cells were grown on glucose to an OD_{600} = 0.5, washed, and shifted to either 0.5 or 2 g l$^{-1}$ acetate at an OD_{600} = 0.25. The experiment was carried out in a chamber heated to 37°C, and the cultures were mixed with a magnetic stirrer. Samples (3 ml) were taken and processed by fast filtration of as described (Bolten et al, 2007) without additional washing of cells. Extraction was carried out by immediately placing the filter in 4 ml of aqueous 50% (v/v) ethanol.
solution heated to 78°C and incubation for 3 min at 78°C. The extraction solution transferred to two 2-ml tubes was centrifuged for 2 min at −15°C at 15,000 g to remove cell debris. The samples were dried (Christ RVC 2-33 CD centrifuge and Christ Alpha 2–4 CD freeze dryer) and resuspended in water. Metabolites were identified and quantified by ultrahigh performance liquid chromatography combined with mass spectroscopy (Thermo TSQ Quantum Ultra triple quadrupole instrument, Thermo Fisher Scientific) as described before (Buescher et al., 2010). Conversion of the OD-normalized metabolite measurements to cellular concentrations was done using the relationship between total cell volume and OD as described before (Volkmer & Heinemann, 2011).

Supplementary information for this article is available online:
http://msb.embopress.org

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Author contributions
OK, BV, and MH conceived and designed the study. BV and JR conducted the experiments and analyzed data. OK developed, implemented, and analyzed the mathematical models. OK and MH wrote the manuscript with input from all authors.

Conflict of interest
The authors declare that they have no conflict of interest.

References


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