Title: Metabolomic rearrangement controls the intrinsic microbial response to temperature changes

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22   *Keywords: temperature shift; Arrhenius; Michaelis-Menten kinetics; thermodynamics;*

23   *entropy; enthalpy; membrane fluidity; proteomics; barcoded transposon mutant libraries;*

24   *Escherichia coli; Bacillus subtilis; Schizosaccharomyces pombe; climate change*

Abstract

The impact of temperature on growth is typically considered under heat- or cold-shock conditions that elicit specific regulation. In between, cellular growth rate varies according to the Arrhenius law of thermodynamics. Here, we use growth-rate dynamics during transitions between temperatures to discover how this behavior arises and what determines the temperature sensitivity of growth. Using a device that enables single-cell tracking across a wide range of temperatures, we show that bacteria exhibit a highly conserved, slow response to temperatures upshifts with a time scale of ~1.5 doublings at the higher temperature, regardless of initial/final temperature or nutrient source. We rule out transcriptional, translational, and membrane reconfiguration as potential mechanisms. Instead, we demonstrate that an autocatalytic enzyme network incorporating temperature-sensitive Michaelis-Menten kinetics recapitulates all temperature-shift dynamics, reveals that import dictates steady-state Arrhenius growth behavior, and successfully predicts alterations in the upshift response observed under simple-sugar or low-nutrient conditions or in fungi. These findings indicate that metabolome rearrangement dictates how temperature affects microbial growth.

Introduction

To proliferate and survive, microbes must integrate a vast array of environmental signals such as pH[1], salt[2], osmolarity[3], and nutrient availability[4]. All of these factors are dependent on the concentrations and identities of extracellular chemical species and are subject to intracellular regulation. By contrast, while growth is critically dependent on the environmental temperature, microbes are unable to regulate intracellular temperature. Enteric bacteria face temperature changes across time scales ranging from minutes (host colonization) to hours or days (fever), and soil and marine species are regularly exposed to daily and seasonal fluctuations. The effects of temperature can be dramatic: the largest determinant of marine bacterial community composition is local sea temperature[5], and long-term temperature changes associated with climate change are thought to substantially impact soil microbial biomass[6]. Despite these fundamental connections, the mechanistic underpinnings of how temperature affects microbial behavior remain unclear.

Most studies of how temperature affects cellular physiology have focused on the regulatory systems that enable survival under heat and cold stress, during which molecular chaperones assist in the folding and unfolding of proteins and RNA[7,8]. While growth rate decreases at extreme, stress response-inducing temperatures[9], there is typically a temperature range over which growth rate increases with temperature in agreement with the Arrhenius Law of equilibrium thermodynamics[10,11], wherein the natural logarithm of growth rate depends approximately linearly on the inverse of the absolute temperature, with a negative slope that can be interpreted as an activation

energy for growth (E_a, equivalent to the barrier for enzyme kinetics)[12]. This temperature-

dependent behavior is highly conserved across diverse bacteria, archaea, yeast, and

mammalian cells[12], with each species exhibiting its own Arrhenius temperature range

and activation energy.

At the molecular level, enzyme catalytic rates increase with temperature until protein

denaturation, with most activation energies between ~5 and 20 kcal/mol[13,14]. The

evolutionary history of the highly conserved adenylate kinase suggests a trade-off

between E_a and melting temperature[12,15], and theoretical work has suggested that

proteome stability sets the upper bound for the growth rate of a given bacterial species.

However, there is no correlation between optimal growth temperature and E_a across

bacteria[10], indicating that E_a is likely influenced by factors other than proteome stability.

In *Escherichia coli*, the Arrhenius range is between 23 °C and 37 °C and E_a is ~13

kcal/mol[11,16], similar to the free energy change from ATP hydrolysis (12–16 kcal/mol)[17],

suggesting that there may be a single rate-limiting enzyme for growth. On the other

hand, theoretical work on cyclical enzyme networks has suggested that E_a arises from

the average of the activation energies over all reactions within the network[18,19]. Most

central dogma processes in *E. coli* have an activation energy between 10 and 17

kcal/mol[12] and the activation energies of growth and of translation *in vivo* are virtually

identical[20]. Whether the temperature sensitivity of growth depends on the details of

metabolism is unclear, although previous studies reported that E_a in *E. coli* is

approximately constant across some nutrient conditions[11,21]. Taken together, what is

limiting for growth across Arrhenius temperatures and what sets E_a for a given species

remain unknown.

Most previous studies of growth in the Arrhenius range have focused on steady-state

growth, rather than how cells respond to temperature changes. An early study of 133

proteins in *E. coli* showed that the concentration of most of these proteins was

maintained across Arrhenius temperatures, suggesting that the proteome may be

largely temperature insensitive[11]. However, other studies found transient changes in the

synthesis of tRNA synthetases after temperature increases[22], and a decrease from

37 °C to 28 °C resulted in significant changes to ~9% of the *E. coli* transcriptome[23],

perhaps reflecting the selection for coupled sensing of changes in temperature and

other environmental variables such as oxygen levels relevant for animal host

colonization[24]. In the few studies examining the growth rate response to temperature

shifts, some report that *E. coli* growth rate responds almost immediately upon

temperature shifts within the Arrhenius range[22,25], while others report much longer time

scales that scale with the final temperature[21].

Many factors could determine the time scale of temperature adaptation. *E. coli* cells

tightly maintain membrane fluidity across all temperatures permissible for growth by

regulating membrane composition[26]. Increased membrane fluidity allows for higher

respiratory metabolic rates[27], but how fluidity impacts growth rate during temperature

shifts is unknown. Growth rate across nutrients correlates with ribosome concentration,

which is optimized through competition between protein and autocatalytic ribosome

synthesis[28,29]. As a result, many models of growth focus on translation as a key growth-

limiting factor[30]. However, this framework is likely inappropriate for understanding

growth rate variations across temperatures, as ribosome concentration is constant

across Arrhenius temperatures[11,31].

Here, we demonstrate that *E. coli* cells exhibit an asymmetric growth-rate response to

temperature shifts within the Arrhenius range: during downshifts, growth-rate rapidly

decreases on the same time scale as that of the temperature shift, while cells gradually

adapt to upshifts on a time scale corresponding to ~1.5 doublings at the steady-state

growth rate of the final temperature, independent of nutrient source. We show that these

responses do not result from proteome or membrane reconfiguration or from

transcriptional regulation, although increased membrane fluidity was lethal at high

temperatures. To interrogate the mechanism underlying growth-rate adaptation to

temperature shifts, we developed an autocatalytic enzyme network model that

incorporates temperature-sensitive Michaelis-Menten kinetics into chained reactions.

The model quantitatively captured the asymmetric responses to up- and downshifts

across Arrhenius temperatures and how carbon source affects the dynamics

immediately after an upshift through changes in the activation energy of growth.

Furthermore, our model successfully predicted the larger initial acceleration and

decrease in upshift response time observed at sub-saturating substrate concentration

compared with saturation. Growth-rate dynamics during temperature upshifts were

highly conserved across diverse *Escherichia* strains/species and the Gram-positive

Bacillus subtilis, suggesting that certain aspects of microbial responses to temperature

shifts and hence features of the underlying metabolic network may be universally

conserved. Moreover, the ability of the model to capture the distinct response of the

fission yeast *Schizosaccharomyces pombe* suggests that temperature adaptation

provides a window into the factors limiting growth.

Results

The activation energy for growth in a rich growth medium is conserved across *E. coli* evolutionary histories

To determine whether evolutionary history impacts temperature sensitivity across strains of a single species, we measured the growth of 12 *E. coli* strains isolated from fecal samples of hosts encompassing a broad range of body temperatures, including ectothermic species such as lizards, wild mammals, household pets, humans, and birds (which have body temperatures as high as 42 °C) (Table S1)[32,33]. Growth rates were significantly higher in the natural isolates compared with laboratory strains (Fig. S1A), which has been attributed to defects in pyrimidine biosynthesis in domesticated *E. coli* strains[34,35]. Despite host body temperatures ranging between ambient and 42 °C, all strains exhibited similar temperature sensitivity profiles, with Arrhenius behavior (linear relationship between ln(growth rate) and $1/T$) between 27 °C and 37 °C (Fig. S1B), consistent with previous studies of *E. coli* and *Salmonella enterica* isolated from pigs, squirrels, and turtles that showed little variation in temperature-dependent growth rates[36]. Interestingly, the highest growth rate occurred at >37 °C for all strains, regardless of the host from which it was isolated (Fig. S1A). The activation energy of growth for the natural isolates varied between 8 and 14 kcal/mol (Fig. S1C), while laboratory K-12 strains exhibited a slightly higher activation energy (~15 kcal/mol) (Fig. S1C–E). Additionally, other laboratory *E. coli* strains (CS109, BL21) possessed activation energies between 11–15 kcal/mol (Fig. S1E). These data suggest that the

thermodynamic properties of *E. coli* growth are conserved and that host body

temperature does not dictate the temperature sensitivity of enteric bacteria.

E. coli exhibits a multi-step acceleration in response to temperature upshifts

To identify the mechanisms underlying the temperature sensitivity of bacterial growth,

we sought to capitalize on approaches that extend beyond steady-state molecular and

batch culture analyses. Methods such as microfluidics that enable single-cell growth-

rate measurements during perturbations have provided new insights into how bacteria

couple proteome allocation to carbon utilization and mechanical forces to growth[3,37,38].

Similar single-cell tracking using a microscopy-compatible temperature controller[39] can

be used to interrogate simple hypotheses about the molecular architecture underlying

temperature sensitivity. For example, if a single enzyme is rate limiting for growth, a

sudden temperature change should result in an immediate change in growth rate

consistent with the activation energy of the enzyme. By contrast, if growth rate is limited

by a host of enzymes or a negative feedback system, then the time scale and dynamics

of adaptation to a temperature shift may be more complex.

To quantify single-cell growth rates during a temperature shift, we previously designed

and built an inexpensive single-cell temperature controller that precisely controls sample

temperature during imaging[39]. Single-cell contours were used to calculate instantaneous

growth rate over time (Methods), measured as $\frac{1}{L}\frac{dL}{dt}$ where *L* is cell length[3,40]. During

steady-state growth, instantaneous growth rate is constant (indicating exponential

growth) and can be maintained for many generations[39,41]. Similar to liquid growth (Fig.

1A, left), single-cell growth rates of *E. coli* MG1655 displayed Arrhenius behavior (Fig.

S2A,B) between 25 °C and 37 °C, and cell morphology was largely maintained (Fig.

S2C,D) across this temperature range, in agreement with previous studies of

Salmonella Typhimirium[42]. Despite slight differences in E_a, single-cell growth rates were

highly correlated with those in liquid culture (Fig. 1A, inset), indicating that both methods

can be used to measure steady-state growth rates throughout the Arrhenius range.

For the minimal model in which growth depends only on a single enzyme whose rate

varies exponentially with the inverse temperature with the same activation energy as

growth, instantaneous growth rate would adapt immediately to the steady-state value

dictated by the current temperature. Hence, the time scale of growth-rate adaptation

would match that of a temperature shift (for our device, ~1 min). Similar behavior is

predicted for a model in which all reactions important for growth have the same

temperature dependence. To test whether such a minimal model applies to *E. coli*, we

monitored the growth of single cells on LB agarose pads during 10 °C temperature

shifts within the Arrhenius range (27 °C and 37 °C). A rapid downshift from 37 °C to

27 °C resulted in a rapid decrease in growth rate with a timescale quantitatively similar

to that of temperature (Fig. 1B), nearly reaching the steady-state growth rate at 27 °C,

and then slowly decelerating toward the new steady state (Fig. 1B). Growth rate

dynamics closely followed those of temperature across a range of downshifts (Fig. S3).

By contrast, temperature upshifts from 27 °C to 37 °C resulted in a slow and

qualitatively distinct response from downshifts, with an initial "spike" that peaked at ~3

min post-shift and subsequent linear acceleration until reaching the 37 °C steady-state

growth rate at ~40 min post-shift (Fig. 1C), a response time (Methods) substantially

longer than the doubling time at 37 °C (~22 min). This behavior indicates that the

minimal model is not generally applicable, and that some aspect of growth cannot

immediately respond as temperature increases.

The response time to a temperature upshift is determined by the steady-state

doubling time at the higher temperature

To identify factors that affect the response time to temperature upshifts, we shifted *E.*

coli from steady-state growth on LB at 27 °C to 30 °C, 33 °C, or 37 °C and monitored

the instantaneous growth rate dynamics of single cells. In each case, the upshift caused

an initial spike and subsequent linear acceleration up to the steady-state growth rate at

37 °C (Fig. 1C,D). However, the time scale of the overall response depended on the

final temperature. When cells were shifted to 33 °C, the response time was longer than

after an upshift to 37 °C, despite the smaller difference in steady-state growth rate

between the initial and final temperature, and the response time for the shift to 30 °C

was even longer (~60 min, Fig. 1D).

To test whether the response is largely determined by the increased growth rate at the

elevated final temperature, we transformed our measurements of growth-rate dynamics,

normalizing time t by the doubling time at the final temperature (τ_D) to obtain the

thermal time t/τ_D (Fig. 1E). After normalizing the change in growth rate by the

difference in steady-state growth rate at the initial and final temperature, we found that

all trajectories collapsed (at least within the noise of our measurements) onto a single

curve, with response time of 1.6±0.2 doublings at the final temperature (Fig. 1F,

Methods). The same collapse was observed for a broad range of temperature upshifts

within the Arrhenius range between steady-state growth rates spanning 0.6 h^{-1} to 2.0 h^{-1}

(Fig. 1F), suggesting a highly conserved behavior.

While these findings suggest that the response time depends entirely on the growth rate

at the final temperature, growth rate and temperature are inherently coupled by the

Arrhenius behavior (Fig. 1A, S1B,E). To uncouple the effects of growth from

temperature, we performed temperature shifts of *E. coli* on LB from 27 °C to 40 °C or

42 °C, temperatures at which the growth rate is nearly identical to that at 37 °C (Fig.

S4A)[16]. An upshift to 40 °C resulted in a spike similar to the upshift to 37 °C, followed

immediately by a deceleration back to the 27 °C growth rate (Fig. S4A) that was likely

due to heat-shock pathway activation. Cells then accelerated to the 40 °C steady-state

growth rate within 35 min, similar to the upshift to 37 °C, corresponding to a response

time of ~1.4 doublings (Fig. S4B). Similar behavior was observed after an upshift to

42 °C (Fig. S4A,B). These data provide further evidence that the response time is set by

growth kinetics at the final temperature.

To determine whether the response to a temperature upshift is specific to LB, we

monitored *E. coli* cells during an upshift from 27 °C to 37 °C while growing on minimal

media supplemented with glucose or glycerol (Fig. 1G). Each normalized growth

trajectory was highly similar to that observed on LB, with a response time of 1.3–1.6

doublings (Fig. 1H); the main difference was the absence of an initial spike (Fig. 1G,H).

The rapid growth rate of *E. coli* on LB is due mainly to the presence of amino acids[43],

and growth on minimal medium supplemented with casamino acids or on glucose

supplemented with L-glutamate produced an initial spike and a response time of 1.3–1.5

doublings (Fig. 1G,H). Thus, the response time is conserved across many growth

media.

Temperature upshift responses are unaffected by oxygen or chaperones

We initially considered the possibility that the delayed response after an upshift is

regulated by the induction of a stress response at a rate set by the doubling time at the

final temperature. For example, an increase from room temperature to 37 °C induces

transcriptional responses associated with oxygen starvation[24]. Moreover, molecular

chaperones account for ~3% of the proteome at 37 °C, suggesting that folding

assistance is important even within the Arrhenius temperature range[16].

To examine the role of oxygen in temperature upshift responses, we subjected MG1655

cells to an upshift from 25 °C to 37 °C on LB under anaerobic conditions (Methods).

Normalized response dynamics were virtually identical to those during an aerobic

temperature upshift, even though the steady-state growth rate at 37 °C was slightly

lower in anaerobic (~1.8 h^{-1}) versus aerobic (~2 h^{-1}) conditions (Fig. S5A,B). Thus, the

presence of oxygen likely has no impact on temperature upshift responses.

The major heat-shock chaperone DnaK increases ~2-fold in concentration between 37 °C

and 42 °C[16], and ΔdnaK cells exhibited substantial growth defects when shifted from

37 °C to 42 °C compared with wild type (Fig. S5C). To quantify the role of heat stress in

upshift responses, we subjected ΔdnaK cells to a temperature upshift from 27 °C to 37 °C

on LB. Despite having a slightly lower steady-state growth rate (1.8 h^{-1}, Fig. S5D) at 37 °C

compared with wild type, in addition to a deceleration after the initial spike (Fig. S5D), the

normalized response time of ΔdnaK cells was nearly identical (~1.7 doublings) (Fig. S5E).

Under nutrient limitation, the enzymes SpoT and RelA produce the alarmone ppGpp,

which signals large-scale transcriptional reprogramming known as the stringent

response that regulates metabolism[44,45]. Temperature increases from the Arrhenius

range (23 °C–37 °C) to 40 °C or 42 °C in E. coli result in a transient increase in

ppGpp[22,46]. To determine whether the stringent response is responsible for the growth

delay during upshifts, we investigated the behavior of a ΔspoT ΔrelA mutant deficient in

ppGpp production[47] (Methods). The double mutant exhibited slight steady-state growth

defects at 27 °C and 37 °C on LB (Fig. S5F). During an upshift from 27 °C to 37 °C, the

double mutant displayed an initial spike similar to wild type, followed by deceleration

back to the steady-state growth rate at 27 °C (Fig. S5F). Cells then accelerated to their

steady-state growth rate at 37 °C with a response time of ~2.3 doublings (Fig. S5G),

somewhat higher than the response time for the parent strain (~1.8 doublings) (Fig.

S5G). During a shift from 27 °C to 42 °C, ΔspoT ΔrelA cells exhibited a very small spike

followed by rapid deceleration from 0.8 h^{-1} to 0.4 h^{-1} (Fig. S5H), consistent with the

transient increase in ppGpp previously observed in these conditions[22,46]. Thus, the

stringent response is important for growth at heat-shock temperatures, and its impact on

the growth response to upshifts suggests that the response time scale is related to

metabolism.

Rapid growth-rate adaptation to high temperature shocks

How *E. coli* growth rate responds on short time scales to heat shock is surprisingly

unknown, despite the abundance of knowledge on regulatory responses[48-51]. To

examine this regime, we monitored the growth of single MG1655 cells during an upshift

from steady-state growth at 37 °C to 40 °C, 42 °C, 43 °C, or 47 °C. An upshift to 40 °C

resulted in an initial ~20% decrease in growth rate, followed by a rapid acceleration after

~13 min back to the steady-state growth rate at 37 °C (Fig. S6A). An upshift to 42 °C

resulted in a larger growth rate decrease (30%), and cells required longer (~20 min) to

recover back to ~90% of the 37 °C steady-state growth rate (Fig. S6A). At 43 °C, the

growth rate decreased by ~40%, then accelerated to an intermediate growth rate (1.6 h^{-1}

^{1}) after 25 min (Fig. S6A). An upshift to 47 °C resulted in rapid deceleration from 2 h^{-1} to

0.5 h^{-1}, without any subsequent acceleration (Fig. S6A). Nonetheless, cells exposed to

short (5 min) or long (36 min) pulses at 47 °C were able to recover back to the 37 °C

steady-state growth rate within 5 and 45 min, respectively (Fig. S6B), indicating that

temperature stress is cumulative and *E. coli* growth is robust to high-temperature

fluctuations.

E. coli **quickly resumes rapid growth after a cold-shock pulse**

Whereas the heat-shock response primarily deals with protein destabilization and

unfolding, the cold-shock response induces expression of a suite of chaperones that

stabilize RNA[7]. Instantaneous growth-rate responses immediately after low temperature

exposure are virtually unknown. Thus, we subjected MG1655 cells growing at 37 °C on

LB to cold pulses at 18 °C, 12 °C, and 0 °C (Fig. S6C–F, Methods). Similar to

downshifts within the Arrhenius range, growth rate decreased rapidly upon the

temperature downshift (Fig. S6C,E). At 18 °C, cells then quickly accelerated from ~0.2

h^{-1} to ~0.4 h^{-1} and remained at that growth rate until the upshift back to 37 °C (Fig.

S6C). At 12 °C, growth rate initially decreased to ~0 h^{-1}, followed by steady acceleration

to ~0.2 h^{-1} until the upshift back to 37 °C (Fig. S6C). When shifted down to 0 °C (Fig.

S6D–F), cells shrank in size, represented by deceleration to a negative growth rate (-1.3

h^{-1}), followed by acceleration to 0 h^{-1} (Fig. S6E). During the upshifts back to 37 °C, there

was a large initial spike followed by linear acceleration back to the steady-state growth

rate at 37 °C over 20 min (Fig. S6E), all without any cell death (Fig. S6F). Thus, *E. coli*

can quickly respond to cold shock pulses and robustly and rapidly exit cold shock.

Downshift pulses reveal dependence on temperature history

Since the response to a downshift occurs within minutes, whereas adaptation to an

upshift requires longer than the doubling time at the final temperature, it is likely that a

component(s) limiting for growth must be produced to attain the steady-state growth

rate at the higher temperature. In the absence of rapid degradation, after a temperature

downshift the level of such a limiting component would represent memory of the growth

state at the higher temperature until it is slowly diluted by growth down to its steady-

state value at the lower temperature.

To evaluate this hypothesis, we monitored MG1655 cells during temperature downshift

pulses from 37 °C to 25 °C and back to 37 °C of varying duration. As we hypothesized,

after a short (10 min) interval at 25 °C, instantaneous growth rate quickly (within <10

min) recovered back to the 37 °C steady state (Fig. 1I), accompanied by a larger spike

than for cells starting from steady-state growth at 25 °C (Fig. 1I). For the longest interval

at 25 °C (30 min), the response time after the upshift back to 37 °C was still faster (~25

min, Fig. 1I) than the steady-state response (~40 min), indicating that cells did not fully

equilibrate to 25 °C 30 min after a downshift from 37 °C, even though growth rate had

largely stabilized. Similar dynamics were observed in downshift pulses from 37 °C to

27 °C (Fig. S7A). Furthermore, cells shifted back to an intermediate temperature (30°C

rather than 37 °C) after 5 min at 23 °C were able to reach the new steady-state growth

rate almost immediately (Fig. S7B). These results suggest that a growth-limiting

component is slowly diluted at the lower temperature, as cells can respond quickly to

temperature fluctuations.

The *E. coli* proteome is mostly invariant across temperatures in the Arrhenius

range

The standard view of growth rate modulation by nutrients is that changes in growth rate

are accompanied by proteome reallocation, whereby certain functional groups of

proteins such as ribosomes shift in relative abundance to optimize growth on the

provided substrates[52]. The prevailing model for growth optimization is that growth rate

and ribosome concentration are directly coupled[30,53,54], due to the limitation that

ribosomes must produce themselves in addition to all other proteins[28,55]. Therefore, we

considered the possibility that the response time to temperature upshifts is determined

by reallocation of the proteome sectors important for growth. Within this picture, the

rapid response to downshifts and the history dependence of growth rate during

downshift pulses might be due to proteins limiting for growth at higher temperatures

being overly abundant during the downshift.

To test this hypothesis, we performed untargeted proteomics on *E. coli* MG1655 during

steady-state growth on three media (LB or minimal media supplemented with glucose or

glycerol) at 25 °C, 30 °C, and 37 °C. Temperatures outside of the Arrhenius range

(16 °C, 43 °C) were also assayed in LB as positive controls for temperature stress-

response pathways. Proteins from two biological replicates for each condition were

extracted and subjected to liquid chromatography tandem mass-spectrometry (LC-

MS/MS, Methods). Of the 4,285 known open reading frames in the *E. coli* MG1655

genome, 1,918 (44.8%) proteins were identified in each of the 22 samples, similar to the

proteome recovery rate of previous studies[56], accounting for ~91% of the total proteome

estimated from ribosomal profiling (Fig. S8A)[57]. Replicates were highly correlated for all

conditions (r=0.96–1.0) (Fig. S8B,C).

We annotated each protein utilizing the Clusters of Orthologous Groups (COG)

database[58], which we modified to 9 groups to include ribosomal proteins and remove

non-bacterial functions (Fig. 2A; Methods). As expected, at 37 °C the ribosomal protein

fraction was positively correlated with the growth rate in each medium (Fig. 2B, light

blue), while the protein fraction associated with energy and metabolism was negatively

correlated with growth rate in each medium (Fig. 2C, light blue). However, the fraction

associated with each functional group was virtually constant across Arrhenius

temperatures in all three media (Fig. 2D,E, S8D), including proteome fractions of each

ribosomal subunit (Fig. S8E). We only observed significant changes for temperatures

outside the Arrhenius range that were consistent with known stress-response pathways

(Fig. S8D,F,G)[16]. Thus, ribosome fraction is unlikely to drive growth rate changes across

temperatures.

The relative abundance of most individual proteins did not change significantly across

temperatures. Only 13 proteins exhibited a >2-fold change between 25 °C and 37 °C

independent of growth medium (Fig. S9). The protein exhibiting the largest change was

the DNA-binding StpA, which increased 14-fold between 25 °C and 37 °C during growth

in minimal medium with glucose (Fig. S9A). Nonetheless, ∆stpA cells exhibited a similar

response to a temperature upshift from 25 °C to 37 °C on LB as wild-type cells (Fig.

2F,G), as did individual knockouts of the three next most temperature-dependent

proteins (Fig. 2F,G), regardless of whether the temperature dependence of their

abundance was positive or negative (Fig. S9). Thus, the E. coli proteome is largely

insensitive to temperature at steady state, and proteins with the largest abundance

changes across Arrhenius temperatures do not impact the growth-rate response to

temperature upshifts.

Transposon mutant library screening did not identify any genes associated with

temperature upshifts

We next sought to identify genes that affect the response to temperature shifts. We

performed a genome-wide screen using a pooled, randomly barcoded transposon

mutant library in *E. coli* BW25113. This library consists of ~150,000 unique mutants,

each with a 20-nt DNA barcode inserted randomly into the genome near the

transposon[59]. By amplifying and sequencing the 20-nt barcodes, the relative abundance

of each mutant can be quantified in high throughput. We grew the library overnight

under selection at 37 °C in LB, passaged it in fresh LB at 25 °C or 37 °C until growth

reached a steady state, and then shifted to 37 °C or 25 °C for 90 min, respectively (Fig.

3A) (Methods). As controls, we also maintained cultures in steady state at 25 °C or

37 °C for 90 min. Cells were sampled 15 min before, at the time of, and 10, 20, 30, 40,

60, and 90 min after the upshift (Fig. 3A). The sample reached the target temperature

within 5 min (Fig. S10A) and optical density was measured at each sampling time point

(Fig. S10B).

No gene disruptions were consistently identified across biological replicates with a

significant fitness defect specific to the temperature upshift (Fig. 3B,C, S10C).

Disruption of four genes (*trmE*, *lon, ndk, yciO*) was deleterious in the upshift experiment

(Fig. 3B), but also in the 25 °C controls (Fig. 3C). Deletion of the genes that were most

deleterious across upshift replicates (*lon, clpP, lepA*) (Fig. 3B,C, S10C) resulted in

growth defects at the single-cell level (Fig. S10D), but the normalized response time to

an upshift was virtually identical to wild type (Fig. S10E). Disruption of four genes

resulted in a fitness defect during the downshift, but not consistently across replicates

(Fig. S10F). Additionally, none of these gene disruptions displayed a monotonic

decrease in fitness after the downshift (Fig. S10F), suggesting that no non-essential

genes are required for downshift adaptation.

While screening of temperature shifts did not uncover any genes of interest, we

reasoned that the initial passaging at 25 °C to reach steady-state growth may have

resulted in the extinction of mutants with growth defects at low temperatures. Therefore,

we compared the relative abundance of each mutant between steady-state growth at

25 °C and 37 °C. The only gene for which disruption was deleterious at 25 °C in both

biological replicates was *uup* (Fig. 3D, S10G). Uup belongs to the ATP-binding cassette

(ABC) protein ABC-F family and has been suggested to directly bind ribosomes and

assist in their assembly[60]. Δ*uup* cells exhibited slight growth defects at both 27 °C and

37 °C (Fig. 3E), and the response time after a temperature upshift was substantially

longer (~2.7 doublings versus ~1.6 for wild type) (Fig. 3F). To examine whether this

difference was general to other ABC-F proteins, we examined knockouts of all other

ABC-F proteins (EttA, YheS, YbiT) in *E. coli*[61]. Δ*ettA, ΔyheS, and ΔybiT* cells exhibited

quantitatively similar responses to wild type (Fig. S10H,I). *uup* overexpression rescues

the growth defect of a Δ*bipA* mutant at lower temperatures[60]; similar to Δ*uup*, growth

rates at 27 °C were lower than wild-type, but Δ*bipA* cells were able to accelerate to the

steady-state growth rate at 37 °C within 40 min, similar to wild type (Fig. S10H). Thus,

while Δ*uup* and Δ*bipA* mutants both have impaired ribosome assembly at lower

temperatures, *uup* likely serves a different function in assembly dynamics. Taken

together, this screen suggests that none of the nonessential genes are responsible for

the delayed growth-rate response to temperature upshifts.

Response to a temperature upshift is largely conserved during antibiotic

treatment

Our transposon mutant library screening was limited to nonessential genes. To

investigate the role of essential genes during temperature upshifts without completely

eliminating cell viability, we treated *E. coli* cells with a variety of antibiotics at sub-

minimum inhibitory concentration (MIC) levels[62] and subjected them to temperature

upshifts from 27 °C to 37 °C on LB. For chloramphenicol, which directly targets the

peptidyl transferase core of the 50S ribosomal subunit[63], growth rate decreased in a

dose-dependent manner at both temperatures (Fig. 3G), but the growth rate response

still required ~1.5 doublings based on growth under treatment at the final temperature

(Fig. 3G,H). Similar behavior was observed for other ribosome-targeting antibiotics: with

fusidic acid, which targets the translocation step in translation[64], and kasugamycin,

which targets translation initiation[65], growth rates were reduced and the overall

response time was 1.6–1.8 doublings (Fig. S11A,B). Response times were also

conserved under antibiotics that target DNA replication (novobiocin) and transcription

(rifampicin), despite large impacts on growth rate in some cases (Fig. S11C,D). Only

triclosan, which targets membrane synthesis, affected the response time, which

increased to ~2.5 doublings (Fig. 3G,H). Large spikes were present even at high

concentrations of triclosan (5, 10 ng/mL, Fig. S11E), while treatment with high

concentrations of chloramphenicol (100 μg/mL) for 15 min was sufficient to eliminate

any spike upon a temperature upshift (Fig. S11E), indicating that the spike requires

active protein synthesis and/or growth.

At high concentrations of fusidic acid (50 μg/mL), growth rate was extremely low at

37 °C and the normalized response time was much shorter than in untreated cells (~0.2

doublings; Fig. S11F,G). Given the severely limited translational capacity despite high

amino acid availability, these changes likely reflect a mismatch between import of

metabolites and the synthesis of enzymes that utilize them. Deletions of *tusA* and *tusB*,

genes encoding sulfur carriers important for tRNA modification[66], caused decreases in

growth rate due to disruption of translational elongation and the normalized response

time was 0.2–0.6 doublings, similar to fusidic acid treatment at high concentrations (Fig.

S11F,G).

Taken together, these results suggest that disruptions in core cellular processes

typically do not alter the normalized response time during temperature upshifts even

with large effects on growth rate, although in certain cases the time scale can be either

elongated (triclosan) or shortened (fusidic acid).

Altered membrane fluidity has little impact on temperature-shift responses

Since treatment with triclosan, which targets the fatty acid synthase FabI[67], resulted in a

modest increase in normalized response time (Fig. 3G,H), we hypothesized that the

delay in growth rate increase upon a temperature upshift might be due to the need to

alter membrane composition. Membrane fluidity is exquisitely regulated in *E. coli*: the

fraction of unsaturated fatty acids decreases with increasing temperature to maintain

viscosity[26,27]. To examine the impact of membrane fluidity on growth-rate dynamics, we

analyzed the behavior of various membrane synthesis mutants during a temperature

upshift from 27 °C to 37 °C on LB. FadR is a positive regulator of *fabB*, which encodes

the major β-ketoacyl-[acyl carrier protein] synthase responsible for elongating

unsaturated fatty acids[68,69], while FabR is a negative regulator of *fabB*[70]. *fadR* and *fabR*

deletions decreased and increased, respectively, mobility within the inner membrane

(Fig. 4A,B) (Methods), as expected. Previous studies suggested that, upon a

temperature upshift, the membrane is overly fluid and its composition is regulated to

restore optimal fluidity[26,27]; we found that inner membrane fluidity 5 min after the

temperature upshift (first measurement time point) was the same as prior to the shift

(Methods) (Fig. 4C), suggesting that regulation of fatty acid composition occurs over a

short time scale (<5 min). Moreover, Δ*fadR* and Δ*fabR* cells exhibited virtually identical

normalized response times as wild type (Fig. 4D,E).

Although membrane composition is regulated to maintain fluidity in wild-type cells,

Δ*fabR* cells grew equally fast at the single-cell level (Fig. 4D) and slightly faster and to a

higher yield than wild type at 37°C in liquid culture (Fig. 4F), in agreement with a

previous study showing that higher membrane fluidity increases growth rate and yield

during aerobic growth due to increased respiratory potential[27]. We reasoned that while

higher membrane fluidity confers a growth advantage in the Arrhenius temperature

range, lack of fluidity regulation may result in fitness defects at temperatures in the heat

shock regime due to membrane instability[71]. To test this hypothesis, we shifted wild-type

and ∆*fabR* cells from steady-state growth at 37 °C to 42 °C or 44 °C. Although both

strains were able to largely recover after a transient growth rate decrease due to the

upshift to 42 °C, ∆*fabR* cells experienced a larger initial decrease and took longer to

recover than wild type (Fig. 4G). Moreover, while wild-type cells maintained growth at

44 °C, ∆*fabR* cells immediately ceased growth and lost turgor pressure within 30 min

(Fig. 4H), presumably due to mechanical defects in the membrane permeability barrier.

Thus, while membrane fluidity does not determine the time scale of upshift responses,

its regulation is critical for cell integrity at high temperatures.

A temperature-sensitive enzyme network (TSEN) model captures temperature-

shift response dynamics

Our findings indicate that the normalized response time to temperature upshifts is

largely conserved (Fig. 1F,H, 2G, 3H, 4E, S5B,E, S10I, S11B,D), but can vary in certain

conditions (Fig. 3F,H, S5G, S11G). Our proteomic, genetic, and chemical screens

largely failed to uncover a key molecular regulator of the response, leaving it unclear

how the response behavior arises and what factors set the time scale. To interrogate

the mechanisms underlying these phenomena, we developed an autocatalytic network

model of growth. Such models have a long history in enzyme kinetics[18], and have

provided a useful framework for understanding emergent behaviors in gene expression

and bacterial growth[19,72,73].

To model growth, we incorporated three general classes of reactions: (1) import, (2)

metabolite production, and (3) volume expansion (Fig. 5A). Each reaction obeys

Michaelis-Menten kinetics, such that metabolite c_i is consumed by enzyme e_i to

produce the next metabolite c_{i+1} in the network:

550
$$c_i + e_i \rightleftharpoons (c_i e_i)^* \longrightarrow c_{i+1} + e_i. \tag{1}$$

551   In a linear network (no branching), the dynamics of each intermediate metabolite are

552   dictated by

553
$$\frac{dc_i}{dt} = \frac{k_{i-1}e_{i-1}c_{i-1}}{K_{i-1} + c_{i-1}} - \frac{k_i e_i c_i}{K_i + c_i} - c_i g, \tag{2}$$

where the first two terms on the right-hand side reflect enzymatic production and

consumption of c_i and the last term accounts for dilution via growth at the rate g (SI). e_i

is the concentration of the ith enzyme, k_i is its catalytic rate, and K_i is its Michaelis-

Menten constant. Importantly, we consider the possibility that both k_i and K_i are

temperature dependent with Arrhenius behavior (Fig. 5A, SI). In support of this

scenario, the Michaelis-Menten constant of several enzymes has been shown to exhibit

Arrhenius behavior[74-76]. After the final step of a reaction network of size N, an enzyme

e_N consumes c_N to expand cell volume at a rate $g = \gamma_0 \frac{k_N e_N c_N}{K_N + c_N}$, where γ_0 is an efficiency

factor assumed to be constant in a given environment, reflecting the conversion of c_N to

a structural component of the cell envelope (SI). From physical considerations of

glucose uptake and growth rate constraints (SI), we estimated that γ_0 is ~0.02 mM^{-1}. We

call these equations a temperature-sensitive enzyme network (TSEN) model.

Since the proteome is largely maintained across temperatures (Fig. 2E, S8D), we

assumed that the concentration of each enzyme remains constant during any

temperature shift. In a simple version of our model with two intermediate metabolites

(minimal TSEN), we considered a single intermediate reaction between import and

growth and set each kinetic parameter to be identical across reactions ($k_i = 1$ min^{-1},

$K_i = 1$ mM at 37 °C, E_a = 15 kcal/mol). We also assumed a high (saturating)

concentration of the external substrate ($c_0 = 100$ mM, $K_0 = 1$ mM) and enzyme

concentrations of 1 mM. At a given temperature, the system reaches a steady state with

stable concentrations of the intermediate metabolite. The catalytic rate of 1 min^{-1} was

chosen for simplicity; increases in k_i that may be more representative of intracellular

enzymatic catalytic rates[77] have no impact on normalized growth-rate responses in the

model (Fig. S12A).

We simulated the model to reach a steady state at 27 °C and then shifted the

temperature to 37 °C. The system exhibited a non-zero response time to reach the

steady-state growth rate at 37 °C (Fig. 5B). To increase growth rate by 95% of the

difference between 27 °C and 37 °C required ~2 doublings (Fig. 5B), similar to our

experimental observations (Fig. 1F,H). Variations in kinetic parameters largely

maintained response times of 1–2 doublings (Fig. S12B). If, however, the E_a for the

catalytic rate of the import reaction dropped below the other catalytic rates (production,

growth), then the response time was instantaneous (Fig. S12B). Moreover, if the

activation energy for all Michaelis-Menten constants is 0, then the growth rate response

is also immediate (Fig. 5B), highlighting the importance of temperature sensitivity of K_i.

Notably, increases in the activation energy of the K_M of the production reaction

produced the largest increase in response times across all activation energies (Fig.

S12B).

To determine the key determinants of the upshift response time, we further simplified

the minimal TSEN to include only two reactions (import, growth) and a single

intermediate metabolite (c_1). This "production-less" TSEN has the benefit of being

analytically tractable, and predicts under a reasonable set of assumptions that the

steady-state concentration of c_1 is $\sqrt{\frac{K_1}{\gamma_0}}$ (SI), indicating that the temperature sensitivity of

c_1 and thus of growth rate is determined by the temperature sensitivity of the Michaelis-

Menten constant K_1. The production-less TSEN predicts that the normalized response

time is only non-zero when K_1 has a non-zero E_a and only weakly depends on E_a above

~20 kcal/mol and K_1 above 10 mM (Fig. S12C–E, SI). Furthermore, the model predicts

that adaptation of the growth rate to 95% or 99% of the difference between steady-state

growth rates at the two temperatures occurs within 0.8 or 1.9 doublings, respectively

(Fig. S12F, SI), consistent with our experimental data and suggesting that the precise

definition of the response time scale is not critical for producing physiological

timescales.

For a reaction network with N intermediates, the analytical solution of steady-state

growth rate (SI) is

611
$$g = \frac{\dfrac{k_0 e_0 c_0}{K_0 + c_0}}{\dfrac{1}{\gamma_0} + \sum_{i=1}^{N} c_i},$$
(3)

which is set by the import rate $\frac{k_0 e_0 c_0}{K_0 + c_0}$, growth efficiency factor γ_0, and the total

intracellular metabolite concentration $\sum_{i=1}^{N} c_i$. Since import changes instantaneously with

temperature, the response time scale is associated with rearrangement of the

metabolome. Eq. 3 also reflects that growth comes at the cost of storing metabolic

intermediates c_i, and holds regardless of branching within the network (SI). This model

recovers the well-known Monod Equation as long as import follows Michaelis-Menten

kinetics[78] (SI), which has been shown for a variety of sugar transporters in *E.* coli[77,79,80].

Eq. 3 also predicts a growth rate in glucose consistent with estimates derived from

glucose uptake rates (SI). Additionally, as metabolite concentrations and import rate

both increase with temperature, the growth rate (g) can exhibit some slight non-

Arrhenius temperature dependence (Fig. S12G).

In *E. coli*, the majority of major metabolites are present at concentrations that saturate

their respective enzymes[81]. However, many central-carbon reactions operate near their

K_M[81], suggesting that bottlenecks are highly likely. Moreover, enzymes that catalyze

product formation tend to have higher activation energy than transporters[82]. Within a

simple network involving import, production, and growth, introducing a bottleneck into

the production reaction characterized by a large and temperature-sensitive K_M

($K_M(T = 37\,°\mathrm{C}) = 20\,\mathrm{mM}$, E_a=22 kcal/mol) produced strikingly physiological behavior:

simulations predicted an initial spike similar to our experimental observations and a

response time of ~2 doublings (Fig. 5B). Moreover, when the bottleneck was within a

pathway involving multiple production reactions, the spike broadened, and the

acceleration dynamics were quantitatively similar to our experimental measurements

(Fig. 5C). This TSEN model readily predicts asymmetric behavior between upshifts and

downshifts (Fig. 5D); such asymmetry is expected from temperature-dependent

Michaelis-Menten kinetics[12]. Additionally, after the initial large decrease in growth rate

upon a downshift, the multiple-reaction model predicts a slow deceleration toward the

slower steady-state growth rate (Fig. 5D, dark blue), similar to our experimental

observations (Fig. 1C, S2). Thus, an initial spike, a physiological response time, and

asymmetric behavior emerge from only a few simple assumptions about the network.

Spike and response time are dictated by metabolome rearrangement

In the bottlenecked TSEN model, metabolites after the bottleneck undergo a transient

decrease in concentration after a temperature upshift (Fig. 5E) that agrees with the time

scale of the spike response (Fig. 5D), suggesting that spikes are caused by rapid

consumption of post-bottleneck metabolites. Meanwhile, metabolites before the

bottleneck gradually build up, as do the post-bottleneck metabolites after the spike, until

metabolome rearrangement has stabilized (Fig. 5E). As a result, final growth rate (which

scales with temperature) dictates the thermally limited response time necessary to

rearrange the metabolome. Simulations of our model captured the near invariance of

the normalized response time across initial and final temperatures (Fig. 5F) as

represented by linear scaling of absolute response time with doubling time at the higher

temperature (Fig. 5G). This scaling was consistent with our experimental measurements

(Fig. 2E), which exhibited a slope of 1.4±0.3 (Fig. 5H), consistent with the range of

normalized response times measured across temperatures and growth media (Fig.

1F,H).

Growth rate follows the Monod Equation in a temperature-dependent manner

Our model indicates that the temperature sensitivity of K_M is a critical determinant of the

response to temperature upshifts, motivating us to broadly explore K_M over

temperatures and nutrients. Early work by Monod and others demonstrated that *E. coli*

growth rate depends on glucose concentration in a manner remarkably similar to

Michaelis-Menten enzyme kinetics with a half-saturation constant K_M~22 μM[78]. This

relationship is referred to as the Monod Equation

$$g = \frac{g_{\max} c}{K_M + c},$$ (4)

where c is the concentration of the substrate (e.g., glucose) and $g_{\max}$ is the growth rate

when $c \gg K_M$. Theoretically, a temperature-dependent K_M should cause the overall

activation energy to decrease at lower substrate concentration, making growth less

temperature sensitive[12]. Previous studies indicated that growth of *E. coli* on simple

sugars generally obeys the Monod Equation[83], with a range of reported K_M values[84]; *E.*

coli growth on acetate has a particularly large K_M~8 mM[85]. The K_M of *E. coli* growth on

glucose is small[86] and has been hypothesized to be invariant across temperatures[84].

The K_M for the growth of nitrifying bacteria on nitrogen is temperature dependent[87], as is

the K_M for the growth of *Methanosarcina barkeri* on acetate[88] and of *Klebsiella*

aerogenes on glucose[89]. Thus, growth rates generally obey Michaelis-Menten kinetics,

with K_M values that can vary over many orders of magnitude and with unclear

temperature dependence.

To examine the temperature dependence of K_M across a diverse range of metabolizable

substrates, we grew *E. coli* MG1655 in MOPS minimal medium supplemented with

simple sugars (glucose, fructose, maltose), succinate, acetate, or casamino acids at

various concentrations and temperatures (25 °C, 30 °C, 37 °C) and quantified maximum

growth rate in liquid culture (Methods). We also measured growth rate across

concentrations of LB, whose average stock amino acid molarity we estimated to be 182

mM (Methods). In glucose, we estimated that K_M at 37 °C was 36±13 µM, in reasonable

agreement with early work by Monod[78] (Fig. S13A–C). At lower temperatures (25 °C,

30 °C), measuring growth rates at concentrations <150 µM was challenging (Fig. S13B),

but our estimated values (Fig. S13C) were in reasonable agreement with the reported

K_M for the glucose-specific transporter PtsG in *E. coli* (60 µM)[79]. In other sugars, we

measured a wide range of K_M values (Fig. S13A,C) consistent with previous studies[80].

For growth on casamino acids or LB, K_M was relatively large and clearly increased with

temperature (Fig. S13A,C). These data indicate that the K_M for non-sugar substrates

can be at least an order of magnitude higher than for simple sugars and temperature

dependent. However, on some substrates K_M remained constant or even decreased

with increasing temperature (succinate, maltose; Fig. S13C).

These measurements also enabled estimation of the activation energy for growth in

each condition (Fig. S13D–G). In glucose, E_a was relatively constant (22±6 kcal/mol)

between 0.17 mM and 11 mM (Fig. S13D,F), which are concentrations >3-fold above

K_M (40-60 µM); this activation energy is substantially higher than in LB. For growth on

acetate, amino acids, and LB, we were able to measure E_a accurately at concentrations

below K_M. On acetate, E_a decreased from 27±6 kcal/mol during growth at saturation to

19±4 kcal/mol at half the K_M (3.8 mM) (Fig. S13F). On amino acids or LB, E_a decreased

from 16±4 kcal/mol or 15±2 kcal/mol, respectively, at saturation to 4±2 kcal/mol at 0.9

mM or 6.5±5 kcal/mol at 0.6 mM, respectively (Fig. S13E,G). Thus, for substrates with

large K_M (>1 mM), the activation energy for growth decreases with concentration, as

expected for simple enzyme behavior[12].

TSEN model predicts spike dependence on nutrient type and the response to a

downshift pulse

Despite the higher temperature sensitivity (E_a) of steady-state growth rate in glucose

compared with CAA or LB, the response time for an upshift was highly similar across

these nutrients (Fig. 1H), as predicted by our TSEN model, wherein increases in the

activation energy of the import reaction have little effect on response times (Fig. S12B).

However, the spike was much smaller or nonexistent in glucose as well as glycerol (Fig.

1H), another condition in which E_a was much larger than in LB (Fig. S13F,G). Motivated

by this decoupling of response time and spike height, we probed the behavior of our

model when changing the activation energy of the catalytic rate of the import reaction to

mimic the differences between LB and glucose. Our model predicts that spike height

should decrease sharply when the activation energy of import is >15 kcal/mol (Fig. 6A).

An increase from 15 kcal/mol to 30 kcal/mol (with all other parameters held constant)

lowered the growth rate at 27 °C by approximately 40% and dramatically lowered the

spike height (Fig. 6B). However, the response time increased by only ~0.1 doubling

(Fig. 6B), as the rest of the TSEN model parameters remained unaltered. Thus, the

model predicts that activation energy differences between nutrient types (Fig. S13F,G)

are sufficient to explain our experimental data for the response dynamics in simple

sugars and lacking amino acids (Fig. 2G,H).

While growth rate rapidly decreases after a downshift in our model (Fig. 5D), the

concentration of metabolites requires dilution to equilibrate, which takes place on the

time scale of growth. Thus, during a transient downshift pulse, the cell gradually

transitions from the high temperature to the low temperature metabolic state. Indeed,

simulations of the bottle-necked TSEN model (Fig. 5C) during a downshift pulse from

37 °C to 27 °C back to 37 °C, with variable duration at 27 °C, resulted in faster upshift

responses than from the steady state at 27 °C (Fig. 6C). More than a doubling at 27 °C

was required for recovery of the upshift response time (Fig. 6D) and the spike height

remained higher than for an upshift from steady state for pulses of multiple doublings

(Fig. 6E), again collectively consistent with our experimental data (Fig. 1I, S7).

These findings highlight the ability of our model to reproduce nearly all observed

temperature-shift responses with reasonable quantitative agreement, and underscore

the importance of the temperature sensitivity of import and metabolome rearrangement

in upshift responses.

TSEN model successfully predicts temperature upshift response at low substrate

concentration

Although we have thus far focused on experimental conditions in which the external

substrate concentration is saturating, nutrient concentrations are low in many

environments[90,91]. Since a key feature of the ability of our model to successfully predict

upshift responses is the temperature sensitivity of Michaelis-Menten constants, we were

motivated to examine the low-nutrient regime. Microbes typically respond to low-nutrient

conditions by upregulating stress response pathways and altering their proportions of

import and biosynthesis enzymes[91,92], but such regulatory mechanisms occur on much

longer time scales than a rapid temperature upshift, hence we kept all parameters in the

model constant besides substrate concentration. We simulated our model with external

concentrations below the K_M for import and considered a temperature upshift from

27 °C to 37 °C. At $c_0 < K_0$, the relative spike height increased substantially, up to 100%

of the steady-state growth rate difference between the two temperatures, and the

normalized response time decreased with decreasing concentration (Fig. 6F–J). This

decrease in response time occurred because the increase in import rate after a

temperature upshift is smaller when $c_0 \leq K_0$ compared with $c_0 \geq K_0$[12], despite an

identical increase in catalytic rates that consume the imported metabolite. The activation

energy for growth was also predicted to decrease with decreasing nutrient concentration

(Fig. 6H), in agreement with our experimental measurements of growth on amino acids

(Fig. S13G).

To test these predictions, we shifted MG1655 cells from 27 °C to 37 °C during growth

on MOPS minimal medium supplemented with a low concentration of casamino acids

(CAA) (Methods). With 4.6 mM CAA, a concentration near the K_M, growth rate

increased from the steady state value at 27 °C (~0.5 h^{-1}) to that at 37 °C (~0.8 h^{-1}) after

only 25 min, corresponding to 0.25 doubling times at 37 °C (Fig. 6K,L). Moreover, the

spike peaked at a growth rate close to that of the 37 °C steady state (Fig. 6K). These

dynamics were in reasonable agreement with the predictions of our model (Fig. 6I,J),

indicating that the response to temperature shift is dictated by the temperature

sensitivity of K_M and its relationship with nutrient concentration.

Diverse bacteria exhibit a characteristic response to temperature shifts

We sought to determine if other strains and species would exhibit similar responses to

temperature upshifts as *E. coli* MG1655 and BW25113. We first examined several *E.*

coli strains during a temperature upshift from 25 °C to 37 °C on LB. *E. coli* CS109, a K-

12 strain that has impaired lipid synthesis and is defective in growth at temperatures

above 37 °C (Fig. S1D,E)[93], exhibited the characteristic spike and linear acceleration

from 0.8 h^{-1} to 1.8 h^{-1} within ~33 min (Fig. 7A), corresponding to a normalized response

time of ~1.4 doublings (Fig. 7B). An *E. coli* isolate from a human fecal sample exhibited

faster steady-state growth rates than MG1655 or BW25113[94], and an upshift caused a

spike and overall increase from 1 h^{-1} to 2.3 h^{-1} within 30 min (Fig. 7A), corresponding to

a normalized response time of ~1.6 doublings (Fig. 7B). *E. coli* isolates from a turtle

(cold-blooded host, strain Ram551) and a seagull (high host body temperature,

Ram1897) displayed similar responses, with a spike and linear acceleration that in total

required 1.5 and 1.7 doublings, respectively (Fig. 7A,B). Additionally, each of these

strains responded to the downshift from 37 °C to 25 °C on the time scale of the

temperature dynamics (Fig. S14). Thus, diverse strains of *E. coli* exhibited a common

characteristic response.

In the gut commensal *Escherichia fergusonii* B253, the temperature shift from 25 °C to

37 °C resulted in a growth rate increase from 1 h^{-1} to 2.3 h^{-1} with a spike and

subsequent linear acceleration over ~30 min (Fig. 7A), corresponding to a normalized

response time of 1.5 doublings (Fig. 7B). In the Gram-positive *Bacillus subtilis* 168, an

upshift from 27 °C to 37 °C produced a large spike from ~0.7 h^{-1} to ~1.3 h^{-1} that

extended several minutes longer than in *Escherichia* strains, and then growth rate

linearly accelerated to ~2.0 h^{-1} (Fig. 7A). The entire response lasted ~45 min, producing

a normalized response time of ~2 doublings (Fig. 7B). Additionally, both species

responded rapidly to downshifts (Fig. S14), similar to *E. coli.* These results suggest that

bacteria generally respond to temperature shifts with a characteristic spike and linear

acceleration requiring 1.4–2 doublings at the final temperature, and that metabolic

differences between phylogenetically diverged species may result in subtle distinctions

in the upshift response.

Temperature shifts in fission yeast produce a distinct response captured by the

TSEN model

We sought to determine if single-celled eukaryotes would respond to temperature shifts

in a similar manner to bacteria. The rod-shaped fission yeast *Schizosaccharomyces*

pombe grows optimally at 32 °C and possesses an Arrhenius range between 22 °C and

32 °C, with E_a~8 kcal/mol in rich media[95]. During an upshift on the rich medium YE5S

from 22 °C to 32 °C, cells exhibited a large growth-rate spike from 0.17 h^{-1} to 0.44 h^{-1},

overshooting the steady-state growth rate at 32 °C (Fig. 7C). This spike was

immediately followed by a deceleration to 0.02 h^{-1}, followed by rapid acceleration to the

steady-state growth rate at 32 °C (~0.4 h^{-1}) (Fig. 7C). The entire response dynamics

lasted ~100 min, corresponding to a normalized response time of ~1.1 doublings (Fig.

7D). Thus, despite decelerating to near growth halting, *S. pombe* cells were able to

reach the steady-state growth rate at the higher temperature more quickly than any

bacteria tested at saturating nutrient concentration.

We wondered whether these differences in behavior were consistent with our TSEN

model. By varying key model parameters and the number of bottleneck reactions, we

identified networks with dynamics upon temperature upshift that closely matched those

of *S. pombe*, with faster normalized response time when the E_a of the bottleneck K_M

was increased to >30 kcal/mol and the bottleneck enzymatic rate was greater than

those of import and growth. Moreover, a TSEN composed of 5 bottlenecked

intermediate reactions resulted in a more pronounced spike and deceleration (Fig. 7D),

similar to our experimental measurements (Fig. 7C,D). The large spike and deceleration

were due to rapid consumption of the network's final metabolite (c_6), which could only

be replenished by upstream bottlenecked metabolites (Fig. 7E). The overall faster

response time was captured by the model and was due to the decrease in steady-state

concentration of c_6 at higher temperature caused by the large E_a of K_M (Fig. 7E),

leading c_6 (which is limiting for growth) to stabilize more quickly.

With the same set of parameters, this TSEN model also predicted an under-shooting to

below the new steady-state growth rate upon a temperature decrease from 32 °C to

22 °C (Fig. 7F), a nonintuitive behavior we confirmed experimentally (Fig. 7F). These

findings suggest that the qualitatively distinct characteristics of the *S. pombe*

temperature shift responses can be captured in a TSEN model by increasing the

magnitude of K_M parameters and the number of bottleneck reactions, and more

generally that the growth network can be tuned to alter the balance between certain

tradeoffs, to accelerate responses at the cost of temporary growth stalling.

Discussion

Here, we used high-precision temperature control and single-cell analyses to show that bacteria exhibit characteristic growth-rate responses to temperature shifts within the Arrhenius range (Fig. 1C, 7A). Temperature upshifts produced a gradual, multi-step acceleration (Fig. 1C), with a normalized response time of ~1.5 doublings at the final growth rate that was invariant across temperatures (Fig. 1F) and substrates (Fig. 1H) and independent of whether there was an initial spike in acceleration, as observed during growth on amino acids but not on simple sugars (Fig. 1H). Moreover, the spike and subsequent linear acceleration as cells transiently grown at 47 °C were returned to 37 °C (Fig. S6B) suggests similar underlying adaptation as for upshifts in the Arrhenius range. Conversely, temperature downshifts produced a rapid deceleration (Fig. 1B, S3, S14). Downshift pulse experiments revealed a memory whereby cells exposed to low temperatures for short durations can respond much more quickly to temperature upshifts (Fig. 1I, S7), an effect that persists for more than a doubling at the lower temperature. Thus, it is likely that some subset of intracellular components changes with temperature and that growth is required to dilute, given the duration required to erase the memory effect.

The maintenance of the proteome across temperatures (Fig. 2) and the conservation of response dynamics during upshifts across mutants (Fig. 2G, 5E, S10I) and antibiotic treatments (Fig. 3H, S11B,D) collectively argue against the existence of a single regulator of growth rate across Arrhenius temperatures. Instead, the ability of our TSEN model to recapitulate nearly all observed behaviors (Fig. 5,6, S12) indicates that

temperature sensitivity of growth is a collective property of the metabolic network. A key

feature is the temperature dependence of K_M, which provides a straightforward

mechanism for the asymmetry between upshift and downshift responses (Fig. 7F): if the

substrate concentration of a reaction is near the K_M at 27 °C (Fig. 7F, blue circle), an

upshift to 37 °C will be accompanied by a small instantaneous growth rate increase

since K_M is higher at 37 °C versus 27 °C; vice versa, a downshift from the K_M at 37 °C

(Fig. 7F, red circle) will result in a larger instantaneous change in growth rate (Fig. 7F).

Each of these instantaneous changes is then followed by an increase (upshift) or

decrease (downshift) in the substrate concentration, and thus the growth rate (Fig. 7F),

as predicted by the TSEN model (Fig. 5E, SI).

To produce the observed initial spike in growth rate, a bottleneck reaction with a large

and highly temperature-sensitive K_M was required (Fig. 5C). Previous measurements of

intracellular metabolite dynamics in *E. coli* grown on glucose showed that reactions in

central carbon metabolism are largely unsaturated and many reactions can exhibit large

K_M values (>1 mM)[81] (Fig. 7G), indicating that the existence of such bottlenecks is

highly likely. There are a large number of potential bottleneck enzymes (Fig. 7G); those

with the largest substrate concentrations are involved in aspartate consumption for

amino acid (*aspC*) and pyrimidine (*pyrB*) biosynthesis, while those with the largest K_M

are involved in threonine (*ilvA*) and serine *(sdaA, ydfG)* degradation. As several of these

reactions are essential, elucidating which reactions are true bottlenecks will likely

require a combination of CRISPRi manipulation of gene expression, direct

measurements of intracellular metabolite concentrations[81], and biochemical

characterization across temperatures.

Although our TSEN model involves 5 parameters per enzymatic reaction, the activation

energies are reasonably constrained by observed measurements (8–30 kcal/mol)[13,96],

and the predicted dynamics are largely insensitive to many of the chosen parameters

(Fig. S12). Furthermore, specific details of the network architecture (e.g., branching)

have no effect on the qualitative predictions of the TSEN model (SI). Most importantly,

the analytically tractable production-less TSEN model predicts that response times are

constrained to 1–3 doublings, regardless of kinetic parameter values (SI).

At steady state, the TSEN model predicts that growth depends only on substrate import

kinetics and the total intracellular metabolite pool (Eq. 3), recovering the empirical

Monod Equation (Eq. 4) and providing a simple framework that connects concentration-

dependent growth directly to measured transporter kinetics[77], thus establishing a simple

mechanism for how Arrhenius-like growth arises across organisms[10]. Our finding that

import K_M values for simple sugars are generally small (<200 μM) and approximately

temperature insensitive (Fig. S13C,F) is in agreement with previous measurements in

glucose[86] and suggests that the activation energy of each rate constant is similar for

simple sugars[12]. However, growth on other carbon sources or amino acids produced

large (1-10 mM) and temperature-sensitive K_M values (Fig. S13C). Why K_M values for

sugars in *E. coli* are temperature insensitive is unclear, although the K_M values for the

vast majority of enzymatic reactions are thought to be temperature sensitive[13]. The

temperature upshift response is predicted to be largely insensitive to the K_M of import at

substrate saturation (Fig. 6F), suggesting that temperature-shift responses are

independent of the details of import kinetics.

A temperature-sensitive K_M predicts that the E_a of growth rate will decrease with

substrate concentration[12] (Fig. 6H), consistent with our measurements of growth on

amino acids (Fig. 6K,L). Such a decrease in temperature sensitivity at low substrate

concentration is predicted by the TSEN to decrease the response time and increase the

relative spike height (Fig. 6F,G,I,J), consistent with our experimental observations that

decreases in amino acid concentrations resulted in faster responses to temperature

upshifts and larger relative spikes (Fig. 6K,L). Thus, microorganisms confronting

nutrient-poor environments may exhibit less temperature sensitivity of growth,

somewhat paradoxically owing to the temperature sensitivity of K_M values.

Additionally, the TSEN model was able to explain qualitatively distinct temperature shift

responses in the fission yeast *S. pombe*, which responded to an upshift with

overshooting and deceleration (Fig. 7C), but which ultimately reached its steady-state

growth rate faster than bacteria (Fig. 7D). The TSEN model predicted that large,

coupled bottleneck reactions account for this behavior (Fig. 7D,E), and such a model

predicted the undershoot response to a temperature downshift (Fig. 7F). In this

scenario, faster temperature-shift responses come at the cost of increasing the

activation energy of growth (Fig. 7C,F), further suggesting tradeoffs between fast

steady-state growth across temperatures and the ability to respond quickly to shifts

between temperatures.

Taken together, these findings suggest that metabolite flux rather than proteome

rearrangement underlies growth rate adaptation across Arrhenius temperatures. As a

result, cells adapt to temperature fluctuations without additional protein synthesis,

resulting in transient memory of previously experienced temperatures (Fig. 2I, S7, 6C–

E). Proteins comprise ~55% of the cell's biomass[97] but constitute a relatively small total

concentration ~7 mM[81] compared with metabolites, which make up ~300 mM despite

being only ~3% of biomass[81,97]. Thus, increasing protein concentrations is metabolically

expensive, and simulations of our TSEN model explicitly including protein synthesis

confirmed that enzyme concentrations remain virtually constant throughout temperature

shifts (Fig. S15). The conservation of growth rate responses across organisms (Fig. 7A–

D), and the ability of the TSEN model to capture diverse responses to temperature

shifts (Fig. 5–7) suggests an evolutionary pressure to adopt this strategy. The ability of

E. coli cells to withstand fluctuations across a large range of temperatures, even short

pulses at heat- and cold-shock temperatures (Fig. S6B,C,E), indicates a robustness that

may be particularly important in the context of host colonization and infection-induced

fevers, and our findings indicate that investigations of temperature adaptation can

provide key insight into the metabolic factors limiting growth.

Acknowledgements

We thank members of the Huang lab for helpful discussions. The *E. coli* BW25113 transposon mutant library was provided by the Deutschbauer lab, with help from Valentine Trotter. This work was funded by a Stanford Interdisciplinary Graduate Fellowship (to B.D.K.), NIH RM1 GM135102 (to K.C.H.) and NSF Awards EF-2125383 and IOS-2032985 (to K.C.H.). K.C.H. is a Chan Zuckerberg Biohub Investigator.

Methods

Culturing conditions and bacterial strains

E. coli wild-type and isolate strains were grown directly from 25% glycerol stocks stored at -80 °C in target media without selection. In typical temperature upshift experiments, cells were grown initially at 37 °C from frozen stocks overnight until saturation, then diluted 1:200 into fresh media at 37 °C until log phase (1.5–2 h in LB, ~4 h in MOPS + glucose). Cells were then diluted 1:10 into fresh media and grown for at least 3 doublings at the lower, target temperature before performing a temperature upshift.

Most mutants (e.g., Keio collection knockouts) were grown from frozen stocks in target media with antibiotic selection. The ppGpp null strain (*spoT::cat, relA::kan*) was grown on LB plates with 10 μg/mL chloramphenicol and 25 μg/mL kanamycin overnight at 37 °C, and individual colonies were selected for further liquid culturing under selection to avoid suppressor mutations.

To evaluate growth kinetics on various media, *E. coli* MG1655 was first grown shaking overnight at 37 °C in MOPS minimal medium (Teknova, Hollister, CA) adjusted to pH 7.2 supplemented with 0.2% (w/v) D-glucose. To measure growth at lower temperatures (25 °C, 30 °C), cells were then diluted 1:200 in fresh MOPS+glucose and grown shaking until saturation for an initial passage at the target temperature. One milliliter of cells were washed in MOPS buffer (pH 7.2) at room temperature and 1 μL was added to 200

μL of target medium in 96-well plates for generating growth curves at the target

temperature in a plate reader.

All strains used in this study are listed in Table S1.

Liquid growth curves and analysis

Growth curves were measured using a protocol developed for accurately determining

growth rates at low optical density[98]. Briefly, 200 μL of medium (without bacteria) were

placed into each well of a transparent 96-well plate (Greiner Bio-One, Monroe, NC) and

sealed with a transparent film (Excel Scientific, Victorville, CA) with holes for gas

exchange cut above each well using a laser cutter (Epilog, Golden, CO). Optical density

(OD) was measured with a BioTek Epoch 2 microplate spectrophotometer (Agilent,

Santa Clara, CA) for at least 15 min to obtain blank values for each well at the target

temperature. The seal was then removed, bacterial samples were added into each well,

and the plate was sealed with a fresh laser-cut transparent film. Linear and orbital

shaking were conducted between OD readings, which were taken every ~7 min. The

OD was corrected for non-linearity (linear range = 0–0.6) via a serial dilution of

concentrated cells and performing a polynomial fit to obtain general fit parameters [98].

For each well, the well-specific blank OD value determined prior to addition of cells was

subtracted from the OD at each time point, which was then used to computed growth

rate as a moving linear regression of the logarithm of the blanked OD.

1007

***E. coli* natural isolates**

E. coli strains from non-human hosts were previously isolated[32,33,99] from fecal samples

collected from a variety of sources, including park and pet store animals and domestic

pets, which were grown on Colilert-18 medium (IDEXX, Portland, ME) for selection of

presumptive *E. coli* colonies[33]. Isolate identities were confirmed by beta-glucuronidase

activity and subsequent sequencing of the corresponding gene, *uidA*[33]. The strains were

grown overnight in a rich medium (LB) at 37 °C, diluted 1:200 in fresh LB, and grown for

24 h across temperatures from 27 °C–47 °C to measure activation energies.

1016

Temperature-controlled single-cell imaging

The temperature control platform, the Single-Cell Temperature Controller (SiCTeC),

was designed and described previously[39]. Briefly, a ring-shaped Peltier module (TE

Technology, Traverse City, MI) was adhered to a glass slide, and the sample

temperature was monitored on the coverslip and controlled using a micro-Arduino with a

proportional-integral-derivative (PID) algorithm. Sample temperature was monitored and

visualized in real time using the open-source software Processing[100]. Agarose

hydrogels were prepared by boiling 3% ultrapure agarose (Sigma Aldrich, St. Louis,

MO) in the target medium, and 200 μL of the mixture were pipetted onto a 9-mm

diameter silicone gasket (Grace Bio-Labs, Bend, OR) onto the temperature-controlled

glass slide. An additional slide was placed on the gasket to compress the hydrogel,

which then cooled and solidified at the initial temperature of the experiment. After

removing the additional compressing slide, 1 μL of cells was pipetted onto the solidified

hydrogel and dried briefly (<1 min) at the initial temperature of the experiment.

1031

Imaging was performed on a Ti-Eclipse microscope in phase-contrast mode using a

40X Ph2 air objective (NA: 0.95) (Nikon Instruments, Tokyo, Japan) with a 1.5X tube

lens. The air objective was used to avoid heatsink issues with oil-immersion objectives.

Images were captured every 30 s on a Zyla 4.2 sCMOS (Andor Technology, Belfast,

UK), Neo 5.5 sCMOS (Andor Technology, Belfast, UK) or PCO Panda 4.2 (Excelitas,

Pleasanton, CA) scientific camera. The microscope system was integrated using

μManager 1.41[101].

1039

Image analysis

To extract cell morphology information throughout the experiment, subpixel-resolution

cellular contours were obtained through a combination of deep learning-based and

traditional image segmentation software[39,102]. Briefly, we first aligned the images using

the Template-Matching plugin in FIJI[103,104], then each image was processed with a fully

convolutional neural network model, *DeepCell*[102]. Separate neural networks were

trained for *E. coli* rich medium, *E. coli* minimal medium, and *S. pombe* rich medium,

with >200 cells manually annotated in each condition[39,40,102]. Outputs from DeepCell

classification were used to extract cellular contours using *Morphometrics* v. 1.1 in

MATLAB (MathWorks, Natick, MA)[105]. Custom MATLAB scripts were used to track

individual cells and measure cellular geometry[40].

1051

Rapid temperature downshifts

To increase the rate of temperature change during downshifts from previous

experiments performed using ambient temperature as the cooling sink, which required

~5 min from 37°C to 27 °C[39], we used dry ice (solid CO_2) to rapidly cool samples.

During a downshift, the SiCTeC device was powered off and a 250-mL beaker with dry

ice was used to pour sublimating dry ice directly onto the sample on the glass slide. For

downshifts to temperatures above ambient, when the temperature was ~1 °C above the

target downshift temperature, the SiCTeC device was powered back on and the PID

algorithm restarted control of the sample temperature. The sample temperature was

closely monitored and adjusted accordingly for undershooting. This method enabled

stabiliziation at the lower temperature within <1 min. For downshifts to temperatures

below ambient, dry ice was continuously poured onto the sample at intervals necessary

to maintain the target temperature. Temperature upshifts back to 37 °C were performed

by turning back on the SiCTeC device.

1066

Anaerobic growth

To perform temperature shifts in anerobic conditions, *E. coli* MG1655 was inoculated

from a frozen stock into LB and grown overnight in an anaerobic chamber (Coy

Laboratory Products, Grass Lake, MI), then diluted 1:200 and grown until saturation in

pre-reduced LB (i.e., kept in chamber for >48 h before culturing). Cells were diluted

1:200 in pre-reduced LB and grown at 37 °C until log phase (~2 h), then diluted 1:10

and grown at 27 °C for 3 h. From log phase at 27 °C, 1 μL was pipetted on a SiCTeC

glass slide for temperature shifts (all components pre-reduced) and imaged inside the

chamber using a Ti-Eclipse inverted microscope (Nikon Instruments, Tokyo, Japan) with

a Neo 5.5 sCMOS (Andor Technology, Belfast, UK). The SiCTeC platform was

controlled by a laptop inside the chamber.

1078

Quantification of response time

To measure the response time of an upshift trajectory, the steady-state growth rate (g^{ss})

at the final temperature was determined by measuring the average of the growth rate

across the timepoints after which growth rate had stabilized (determined by visual

inspection). Its error (δg^{ss}) is defined as the standard error of the mean. This steady-

state growth rate was subtracted from the entire trajectory ($g(t) - g^{ss}$), and the

response time was determined as the time (t) at which $g(t)$ was indistinguishable from

g^{ss} within error (δg^{ss}), which was generally ~5% of g^{ss}.

1087

Antibiotic treatment during single-cell temperature shifts

Five-hundred microliter aliquots of growth medium+3% ultrapure agarose were melted

at 95 °C, then mixed with 0.5 µL of 1000X target concentration antibiotic stock solution

and 150 µL was immediately used to make a hydrogel for the sample as described

above. The short time exposed to higher temperatures (~30 s) likely only moderately

impacted the minimum inhibitory concentration, as antibiotic efficacies against *E. coli*

are unaffected by long-term (30 min) treatment at 56 °C, with many drugs unaffected by

autoclaving (121 °C)[106].

1096

Liquid culture samples for proteome extraction

1098   *E. coli* MG1655 was grown at 37 °C overnight in MOPS buffer (Teknova, Hollister, CA)

1099   adjusted to pH 7.2 supplemented with 0.2% (w/v) of carbon source (glucose or glycerol)

1100   (Sigma-Aldrich, St. Louis, MO) or LB (Thermo Fisher Scientific, Waltham, MA), then

diluted in duplicate and grown for at least 4 doublings at the target temperature (25 °C,

30 °C, or 37 °C). Growth at additional temperatures (16 °C, 43 °C) were assayed for LB.

Cultures were grown to log phase (OD_{600}~0.2) in 50-mL Falcon tubes and 15 mL were

harvested and washed with 1 mL PBS via centrifugation at 4 °C. Supernatant was

removed and the pellet was snap-frozen with liquid nitrogen.

Proteome extraction

Extraction was performed as previously described[107]. Briefly, samples were thawed and

lysed using a bead-beating procedure, then supernatant was reduced and alkylated with

DTT and iodoacetamide, respectively. Peptides were then washed, digested, and eluted

using S-trap tubes (Protifi) and desalted with C18 solid-phase extraction (Sep-Pak

Waters). Finally, peptides were dried by vacuum centrifugation and quantified for

normalization (Nanodrop ND-1000).

Proteomic analysis via LC-MS/MS and database searching

Peptide quantification was performed as previously described[107]. Briefly, dried peptides

were diluted in 0.2% formic acid to a final concentration of 0.5 μg/mL, then separated by

reversed-phase chromatography (Dionex Ultimate 3000 HPLC, Thermo Fisher

Scientific, Waltham, MA) and directed to a LTQ Orbitrap Elite mass spectrometer

(Thermo Fisher Scientific, Waltham, MA). The top 20 ions were selected for

fragmentation using collision-induced dissociation (DIC), and fragments were analyzed

in the ion trap with rapid scan rate.

1124 Mass spectra were searched against the UniProt canonical *E. coli* FASTA database

1125 using the SEQUEST algorithm of Proteome Discoverer 2.2.0.388. Peptides were filtered

1126 using Percolator with the protein false discovery rate set to 1%. Protein abundance was

1127 based on precursor ion peak areas.

1128

Proteome data analysis and annotation using Clusters of Orthologous Groups

(COG)

Protein functional annotation was performed using the Clusters of Orthologous Groups

of proteins (COG) database[58]. UniProt accession codes were mapped to the COG

database downloaded from https://ftp.ncbi.nih.gov/pub/COG/COG2014/data/. The

corresponding gene of each protein was annotated using the gene association table

from EcoCyc (https://ecoliwiki.org/gaf/gene_association.ecocyc.gz)[108]. Further analysis

was performed using custom MATLAB scripts, wherein the relative abundance of each

protein was calculated for each sample and its replicates and then compared across

conditions.

1139

E. coli **transposon library temperature shifts**

One milliliter of a pooled library of *E. coli* BW25113 transposon insertion mutants with

random DNA barcodes[59] was thawed and diluted into 50 mL of LB+25 μg/mL

kanamycin (Sigma Aldrich, St. Louis, MO) in a 250-mL Erlenmeyer flask (Pyrex,

Glendale, AZ) and grown shaking overnight at 37 °C. 0.5 mL of the stationary-phase

library cultures were diluted into 50 mL of LB in technical replicates at 25 °C and 37 °C.

1146

The 25 °C culture was grown for 3 h to early log phase (OD_{600}~0.15) and 6 mL were

diluted into in each of two flasks containing 50 mL fresh LB pre-warmed at 25 °C, then

grown for another 3 h in an air-heated shaker (New Brunswick Scientific, Edison, NJ).

The temperature upshift from 25 °C to 37 °C was performed by placing one of the 25 °C

flasks into a heated water shaker at 37 °C. The control sample was left at 25 °C.

Samples were collected in 1.5-mL aliquots and flash-frozen using liquid nitrogen every

10 min at timepoints of -10, 0, 10, 20, 30, 40, 60, 90 min relative to the shift (control

samples without temperature shifts were also taken at the same time points).

1155

The 37 °C culture was grown for 2 h until mid- to late-log phase (OD_{600}~0.3) and 1.5 mL

were diluted into each of two flasks containing 50 mL of fresh LB pre-warmed at 37 °C,

then grown for ~1 h in a heated water shaker. For the temperature downshift from 37 °C

to 25 °C, one of the flasks was first placed into a room-temperature water bath for 6 min

for faster cooling, then transferred to an air-heated shaker at 25 °C. The other flask was

maintained at 37 °C as a control.

1162

Each set of downshift/upshift experiments was performed twice, and all samples were

flash frozen and immediately stored at -80 °C. Optical density was monitored at each

time point for all experiments with a Genesys 20 spectrophotometer (Thermo Fisher

Scientific, Waltham, MA). The time scale of the temperature upshift was estimated to be

~3.5 min using a virtual experiment with 50 mL of water in a flask, whose temperature

was directly monitored during a shift from 25 °C to 37 °C using the SiCTeC device

thermistor reading. A similar test was performed for the 37 °C to 25 °C downshift by

placing a 37 °C flask with 50 mL of water into a stationary water bath at room

temperature, giving an estimate of ~6 min to complete the temperature shift.

1172

E. coli transposon mutant library sequencing and analysis

Barcode sequencing (BarSeq) was performed as previously described[59]. Briefly,

genomic DNA was extracted using the DNeasy 96 Blood and Tissue kit (Qiagen) and

quantified using the Quant-iT dsDNA BR Assay kit (Qiagen). BarSeq PCR was

performed using 200 ng of genomic DNA template in 150-μL reaction volumes with Q5

polymerase (with enhancer) (New England Biolabs, Ipswich, MA), 20 μM universal

forward P5 primer, and 20 μM reverse P7 primers with 6-bp TruSeq indices that are

automatically demultiplexed by Illumina software. PCR products were checked for

completion using gel electrophoresis, and 10 μL of each reaction product were pooled

and purified using the Zymo DNA Clean and Concentrator kit (Zymo Research, Irvine,

CA). Sequencing was performed at the Chan Zuckerberg BioHub facility on an Illumina

NextSeq 550 platform in High Output mode.

1185

BarSeq analysis was performed as previously detailed[59], with relevant scripts at

https://genomics.lbl.gov/supplemental/rbarseq/. Briefly, barcode reads were mapped to

their corresponding genomic loci using sequencing of the transposon insertions in the _E._

coli library, and genes were filtered for those with ≥10 barcodes in the central (10–90%)

portion of the gene. Temperature-shift samples were analyzed along with their

corresponding unshifted control samples, with the time-zero sample corresponding to

when the library was shifted (_t_=0 sample). The fitness of each mutant was measured as

the $\log_2$ fold-change in its relative abundance, and further analysis was performed using

custom MATLAB scripts.

1195

FRAP measurements

E. coli cultures were grown overnight from frozen stocks at 37 °C in LB, with 25 µg/mL

kanamycin selection for Δ*fabR* and Δ*fadR* mutants, and then diluted 1:200 into fresh LB

and grown until log phase at 37 °C (~2 h). Cultures were then diluted 1:10 into fresh LB,

and 2 µL of 0.5 mg/mL MitoTracker Green (Thermo Fisher Scientific, Waltham, MA)

were added. The culture was grown at the target temperature for 30 min to enable

sufficient membrane labeling. Five hundred microliters of stained cells were washed via

centrifugation (30 s at 7000 rcf) in fresh LB at the target temperature (37 °C or 27 °C).

One microliter of washed culture was placed on an LB 3% agarose hydrogel and

prepared for imaging using standard glass slide technique. Imaging was performed with

a Zeiss LSM 880 confocal microscope with an environmental chamber for monitoring

and controlling temperature (37 °C) and integrated with the ZEN software suite (Zeiss,

Oberkochen, Germany). Temperature upshift experiments were performed by placing

the sample into the heated environmental chamber for 5 min before imaging.

Fluorescence recovery after photobleaching (FRAP) of individual cells was performed

with excitation at 488 nm using the ZEN software by choosing a photobleaching region

near cell tips covering 1/4 to 1/3 of the cell. The entire cell was imaged at minimum

frame intervals (150–300 ms) to image fluorescence recovery.

1214

FRAP analysis and viscosity estimate

Individual regions of interest were manually delineated for the photobleached cell tips

and the entire cell in FIJI[104], and the total fluorescence of each area was quantified at

each time point. These data were imported for further analysis in MATLAB. The

fluorescence recovery in each photobleached region was corrected by the rate of

photobleaching in the entire cell, and the recovery curve was normalized and fit to the

exponential function $(1 - e^{-\frac{t}{\tau_D}})$. The time constant (τ_D) was used to estimate a diffusion

coefficient (D) via solution to Gaussian photobleaching in a plane, $\tau_D = \frac{r^2}{4D}$ (i.e.,

modeling the cell tip as a disk of radius r on the membrane)[109]. The viscosity (η) was

calculated using the Stokes-Einstein equation $(\eta = \frac{k_B T}{6\pi R D})$, where R is the radius of the

fluorophore (estimated as 2 nm).

1226

***Schizosaccharomyces pombe* culturing**

S. pombe WT972 h- was grown from a frozen stock on YE5S plates (5 g/L yeast

extract, 30 g/L glucose, 225 mg/L each of adenine, histidine, leucine, uracil, and lysine

hydrochloride, 2% Difco Bacto Agar). A single colony was grown at 22 °C or 32 °C in

liquid YE5S overnight until saturation, then diluted 1:100 and grown until log phase

(OD_{600}~0.3–0.5). One microliter of log-phase cells was placed on a 3% agarose YE5S

pad at the initial temperature of the experiment for imaging.

1234

Estimate of LB molarity

LB is largely comprised of free amino acids, and measurements of *E. coli* auxotrophy

and direct HPLC quantification[108] have provided an estimate of ~122 g/mol for its free

amino acid content. The molar mass of tryptone is reported by the manufacturer to be

71.08 g/mol (Thermo Fisher Scientific, Waltham, MA). As LB is composed of 10 g

tryptone and 5 g yeast extract dissolved in 1 L H_2O, we estimate that the concentration

of metabolizable free amino acids in LB is ~182 mM. Note that the accuracy of this

estimate is not critical for any of our conclusions; the value simply enables plotting LB

concentrations on the same plot as other substrates such as casamino acids.

1244

Measurements of K_M

E. coli MG1655 was grown overnight until saturation in MOPS buffer+0.2% (w/v)

glucose at the target temperature (25 °C, 30 °C, 37 °C), then washed twice in MOPS

buffer before being diluted 1:200 in the target medium at the target temperature. Liquid

culture growth curves were obtained as described above. Optical density (OD) was

measured using a microplate reader and maximal growth rate was quantified as the

peak of the derivative of ln(background-subtracted OD)[98]. A weighted fit was performed

on the growth rate versus concentration curve using the Monod equation (Eq. 4) to

extract an estimate of K_M with a standard error. We note that it was challenging to

obtain growth rates at low concentration for simple sugars (e.g., glucose, fructose), due

to both the low K_M and generally low growth rate (<0.2 h^{-1}) (Fig. S13A–C). In succinate,

the relationship between ln(growth rate) and 1/T appeared bilinear, thus a linear fit

produced an estimate of E_a with very large standard error (19±14 kcal/mol) (Fig. S13G).

Figures

1259

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1261   **Figure 1: *E. coli* responds asymmetrically to temperature shifts, and upshift**

1262   **dynamics are determined by the steady-state growth rate at the final temperature.**

A) (Left) Arrhenius plot illustrating that the natural logarithm of *E. coli* MG1655 maximal growth rate for temperatures between 25 °C and 37 °C varies linearly with the inverse absolute temperature, with a negative slope whose magnitude is the activation energy (E_a). (Right) Liquid-culture and single-cell growth rates were highly correlated for temperatures in the Arrhenius range between 25 °C and 37 °C (data from Fig. S1C,E).

B) Single-cell growth rate (blue) of *E. coli* MG1655 throughout a temperature (black) downshift from 37 °C to 27 °C in rich growth medium (LB) (n=253 cells). The curve is the mean growth rate and the shaded region represents one standard error of the mean (SEM) Growth rate responds quickly to the downshift.

C) Single-cell growth rate (red) of *E. coli* MG1655 throughout a temperature (black) upshift from 27 °C to 37 °C in LB (n=792 cells). The curve is the mean growth rate and the shaded regions represent ±1 SEM. Growth rate initially spikes (dark red), followed by linear acceleration (green) to the new steady-state value over ~35 min.

D) Single-cell growth rate of *E. coli* MG1655 throughout a temperature upshift from 27 °C to 30 °C (blue, n=253 cells), 33 °C (purple, n=754 cells), or 37 °C (red, n=904 cells) in LB. Vertical dashed lines indicate the time at which the growth rate reached its steady-state value at the higher temperature. Curves show the mean growth rate and the shaded regions represent ±1 SEM.

E) The thermal time is defined as the time (t) measured in units of doubling times (τ_d) of steady-state growth at the higher temperature. The normalized growth rate is defined as the difference between the growth rate at time ($g(t)$) and the growth

rate at the temperature shift ($g(0)$) divided by the difference between the steady-

state growth rate at the higher temperature (g_{ss}) and the initial temperature ($g(0)$).

F) Normalized single-cell growth rate of *E. coli* MG1655 grown in LB exhibits a

characteristic response with respect to thermal time for shifts between two

temperatures in the Arrhenius range 23 °C–37 °C (n=253–904 cells). Curves

represent the mean, and error bars have been omitted for ease of viewing.

G) Single-cell growth rate of *E. coli* MG1655 throughout a temperature upshift from

27 °C to 37 °C in LB (red, n=792 cells), casamino acids (green, n=270 cells),

glucose (blue, n=353 cells), glucose+glutamate (orange, n=220 cells), or glycerol

(purple, n=520 cells). Curves show the mean growth rate and the shaded regions

represent ±1 SEM.

H) Despite the wide variation in absolute growth-rate responses (G), normalized

growth rate followed an approximately conserved trajectory versus thermal time

across nutrient environments.

I) Single-cell growth rates of *E. coli* MG1655 in LB grown to steady state at 37 °C

and then subjected to pulses at 25 °C for 10 min (red, n=1015 cells), 20 min

(orange, n=1022 cells), or 30 min (purple, n=586 cells). Vertical dotted lines

represent the times at which cells were subjected to the downshift to 25 °C for

the 10- and 20-min pulses. The upshift from steady-state growth at 25 °C to

37 °C is also shown for comparison (blue, n=773 cells). Curves show the mean

growth rate and the shaded regions represent ±1 SEM.

1307

Figure 2: The delayed response to a temperature upshift is not due to proteome

rearrangement.

A) The *E. coli* proteome at 37 °C varies across media. Functional proteomic sectors

(pie chart) were annotated according to the Clusters of Orthologous Groups

(COG) classification (Methods).

B) Ribosomal protein fraction increased with growth rate across media

(M9+glycerol, M9+glucose, LB), independent of growth temperature.

C) Energy and metabolism protein fraction decreased with growth rate across media

(M9+glycerol, M9+glucose, LB), independent of growth temperature.

D) The *E. coli* proteome in LB is largely invariant across temperatures in the

Arrhenius range (25 °C–37 °C).

E) The proteome fraction accounted for by each functional category was

approximately constant in LB across Arrhenius temperatures. Colors correspond

to the functions in the legend in (A).

F) Temperature-upshift (27 °C to 37 °C) responses of individual deletion mutants of

the four most abundant of the proteins whose relative abundance scaled with

temperature across all media conditions. (blue: parent strain wild-type BW25113,

n=710 cells; purple: $\Delta nemA$, n=1052 cells; red: $\Delta stpA$, n=588 cells; orange: Δgcd,

n=814 cells; green: $\Delta ompT$, n=324 cells). Curves show the mean growth rate and

the shaded regions represent ±1 SEM.

G) Normalized growth rate followed an approximately conserved trajectory versus

thermal time across the mutant growth data in (F).

1330

Figure 3: Response time is unaffected by almost all genetic and chemical

perturbations.

A) Schematic of temperature-shift experiments screening a pooled library of *E. coli* BW25113 randomly barcoded transposon mutants (Methods). The library was initially grown in a 50-mL volume at 37 °C, then diluted and grown to steady state at the initial target temperature (25 °C or 37 °C) before shifting to 25 °C or 37 °C at time *t*=0. The optical density was monitored at each sampling time point (~10 min intervals). The fitness of each mutant is defined as the $\log_2$(relative abundance compared to *t*=0) (Methods). This experiment was carried out twice.

B) Trajectories of mutant fitness during a shift from 25 °C to 37 °C (gray vertical bar denotes timing of the shift). Mutants with fitness<-1 when averaged over time points are highlighted in red.

C) Trajectories of mutant fitness during steady-state growth at 25 °C. Mutants with fitness<-1 when averaged over time points are highlighted in blue. (B) and (C) are from the same experiment, and outlier mutants in the upshift (B) were also outliers in the control (C).

D) Trajectories of $\log_2$(relative abundance) during steady-state growth at 25 °C

compared with at 37 °C. A single gene, *uup*, had fitness<-1 when averaged over

time points.

E) Single-cell growth rate of Δ*uup* (red, *n*=609 cells) and its parent BW25113 (blue,

n=734 cells) throughout a temperature shift from 27 °C to 37 °C. Curves show

the mean growth rate and shaded regions represent ±1 SEM.

F) Normalized growth rate versus thermal time for each trajectory in (E) shows that

Δ*uup* cells respond more slowly to an upshift.

G) Single-cell growth rates of *E. coli* MG1655 in LB treated with 0.1 μg/mL

chloramphenicol (orange, *n*=264 cells), 0.5 μg/mL chloramphenicol (dark red,

n=382 cells) or 2.5 ng/mL triclosan (green, *n*=266 cells) throughout a shift from

27 °C to 37 °C. The untreated control is also shown for comparison (blue, *n*=792

cells). Curves show the mean growth rate and shaded regions represent ±1

SEM.

H) Normalized growth rate followed a similar trajectory versus thermal time as the

control for the chloramphenicol treatment data in (G), while triclosan slightly

delayed the growth-rate response.

1364

Figure 4: Changes in membrane fluidity do not alter the response to temperature upshift but increase lysis at high temperatures.

A) FRAP recovery dynamics of the membrane dye MitoTracker in the parent strain BW25113 (blue, n=19 cells), the high-fluidity mutant Δ*fabR* (red, n=15 cells), and the low-fluidity mutant Δ*fadR* (purple, n=14 cells) grown on LB (Methods). Curves show the mean recovery and shaded regions represent ±1 SEM.

B) Membrane viscosity (Methods) was significantly lower and higher in Δ*fabR* and Δ*fadR*, respectively, compared with the parent. Significance was determined using a two-sample t-test; *: $p<0.05$, **: $p<0.005$.

C) Membrane viscosity of *E. coli* BW25113 cells after an upshift at *t*=0 from 27 °C to 37 °C in LB (Methods). Points are estimates from a best fit (Methods) and error bars represent 1 standard error. Dotted line is the mean viscosity from steady-state measurements (B), and the shaded region represents ±1 standard deviation.

D) Growth rate responses of *E. coli* BW25113 (blue, *n*=686 cells), Δ*fabR* (red, *n*=924 cells), and Δ*fadR* (purple, *n*=409 cells) to a temperature upshift from 27 °C to 37 °C in LB. Curves show mean growth rate and shaded regions represent ±1 SEM.

E) Normalized growth rate followed a similar trajectory versus thermal time among the mutants and parent for the data in (D).

F) Growth curves of wild-type (BW25113) (blue) and Δ*fabR* (red) cells grown in LB at 37 °C (*n*=3 replicates). Optical density (OD) was corrected for non-linearity at high OD values (Methods). Maximum growth rates are the mean across replicates and the error is ±1 standard deviation.

G) Growth rate response to a temperature upshift from 37 °C to 42 °C in *E. coli* BW25113 (blue, *n*=1011 cells) and Δ*fabR* (red, *n*=554 cells). Both strains exhibited an initial decrease in growth rate followed by recovery to the steady-state growth rate at 37 °C, but recovery was more delayed for the high-fluidity Δ*fabR* mutant. Curves show mean growth rate and shaded regions represent ±1 SEM.

H) (Left) Representative images of Δ*fabR* cells throughout a temperature upshift from 37 °C to 44 °C. At 37 °C, morphology and growth were wild-type-like (top

1397   left). Growth halted immediately after the shift to 44 °C (top right), with loss of

1398   turgor and cell death occurring within 30–40 min after the shift (bottom left, right).

1399   (Right) Representative images of wild-type MG1655 cells before and after an

1400   upshift from 37 °C to 44 °C. Cells maintained growth and shape.

1401

Figure 5: A temperature-sensitive enzyme network (TSEN) model recapitulates

temperature-shift behaviors through metabolome rearrangement.

A) (Upper left) In the TSEN model, the import reaction (blue), production reactions

(dark red), and volume growth reaction (green) are chained Michaelis-Menten

reactions. (Upper right) The rate equation for each intermediate metabolite (c_i)

involves enzymatic production from c_{i-1} by enzyme e_{i-1} (blue), enzymatic

consumption by enzyme e_i (red), and dilution by volume growth g (green). The

final intermediate c_N is translated into volume growth with an efficiency factor γ_0

(green box). Each kinetic parameter is assumed to be temperature sensitive

according to an Arrhenius equation with activation energy E_a (yellow box). A

minimal TSEN model (TSEN$_{minimal}$) has a single intermediate production reaction

(red), such that the network has only 2 intermediate metabolites (c_1, c_2; gray

box).

B) Normalized growth rate versus thermal time from simulations of a minimal TSEN

model with (blue) and without (black) a temperature-sensitive Michaelis-Menten

constant (K_M) throughout a temperature shift from 27 °C to 37 °C. All other model

parameters are identical and are defined in the panel inset. The TSEN with a

temperature-sensitive K_M results in a non-zero response time (blue). A TSEN

model with a bottleneck (dark red, $K_M = 20$ mM, $E_a = 22.5$ kcal/mol) produces an

initial spike.

C) A TSEN model with a single bottleneck (red, P_3) embedded within a 7-reaction

chain produces a quantitatively similar response to an upshift from 27 °C to 37 °C

as *E. coli* MG1655 cells on LB (purple, *n*=792 cells; shaded region represents ±1

SEM). All other reactions have parameters identical to the minimal model without

a bottleneck (blue) in (B).

D) Normalized growth rate in simulations of the bottlenecked TSEN model in (C)

throughout an upshift (dark red) or downshift (light blue) between 27 °C and

37 °C. In contrast to the spike and slow response to the upshift, the downshift

results in immediate deceleration to a growth rate close to the steady-state value

at 27 °C, followed by slow deceleration to new steady-state value. Overlaid are

the normalized growth rates of *E. coli* MG1655 subjected to an upshift (red, 27 °C

to 37 °C, n=792 cells) or downshift (blue, 37 °C to 27 °C, n=253 cells). Shaded

error bars represent ±1 SEM.

E) The TSEN model in (C) predicts that metabolites upstream of the bottleneck

($c_{1,2,3}$) will have lower concentrations than those after the bottleneck ($c_{4,5,6}$) and

increase slowly on the time scale of growth after an upshift. Post-bottleneck

metabolites undergo transient decreases immediately after the temperature

upshift over a time interval corresponding to the spike (red box). After this initial

period, all metabolites increase to new values corresponding to the steady state

at the higher temperature.

F) The TSEN model in (C) predicts highly similar responses of normalized growth

rate with thermal time for upshifts from 27 °C to 30 °C (blue), 33 °C (purple), or

37 °C (red).

G) Over a broad range of final temperatures, the absolute upshift response time

(time to reach 98% of the difference between steady-state growth rates) has

linear scaling with the doubling time at the final temperature. Each line

represents simulations from a given initial temperature to temperatures up to

37 °C.

H) Experimental estimates of absolute response time follow a linear scaling with

doubling time at the final temperature, similar to simulations in (G). Shown are

data for upshifts involving initial and final temperatures ranging between 23 °C

and 37 °C (data from Fig. 1F–H).

1454

Figure 6: TSEN model predicts changes to upshift response during growth on simple sugars, after a downshift pulse, and at low nutrient concentration.

A) The bottlenecked TSEN model in Fig. 5C predicts that spike height after a temperature upshift will decrease with the activation energy of import. The activation energies of all other reactions were set to 15 kcal/mol (gray circle).

B) Increasing the activation energy of import to $E_a = 30\,\mathrm{kcal/mol}$ based on our experimental measurements of the activation energy of growth in glucose (Fig. S12G) dramatically reduced the spike height (green) compared with our default $E_a = 15\,\mathrm{kcal/mol}$ (red) without affecting the response time, similar to our experimental measurements of the normalized growth-rate response on glucose (green data, same as in Fig. 1H).

C) The bottlenecked TSEN model predicts that short downshift pulses from 37 °C to 27 °C (purple, red, orange) will cause larger spikes and faster recovery to the steady-state growth rate at 37 °C than an upshift from steady state at 27 °C to 37 °C (blue), similar to our experimental observations (Fig. 1I).

D,E) The bottlenecked TSEN model in Fig. 5C predicts that the response time decreases for downshift pulses of duration <1 doubling at the higher temperature (D) and that the spike height remains high for pulses of duration multiple doublings at the higher temperature (E).

F,G,H) The bottlenecked TSEN model in Fig. 5C predicts that response time decreases (F), spike height increases (G), and growth activation energy decreases (H) when nutrient concentration is reduced from above (saturated, red circle) to below (unsaturated, purple circle) the K_M for import (gray vertical bar).

I) Simulations of the bottlenecked TSEN model in Fig. 5C throughout an upshift from 27 °C to 37 °C for high (c_0=5 mM, red) or low (c_0=0.5 mM, purple) external substrate concentration ($K_M^{(import)}$ = 1 mM). The absolute spike height is similar in magnitude at both concentrations, but the steady-state growth rate at 37 °C is much lower for lower external substrate concentration (purple) and is reached more quickly after the upshift than for higher concentration (red).

J) The normalized growth rate calculated from simulations in (H) has a larger spike and a faster normalized response (<1 doubling) for low external substrate concentration (purple) compared with the TSEN model at saturation (red).

K,L) Growth rate throughout an upshift from 27 °C to 37 °C of *E. coli* MG1655 grown on MOPS+46 mM casamino acids (red, *n*=116 cells) or 4.6 mM casamino acids

(purple, *n*=261 cells) exhibits similar dynamics in both absolute (J) and

normalized (K) terms as the simulations in (H,I). Curves are mean growth rate

and shaded regions represent ±1 SEM. The response time at low casamino acid

concentration is much shorter (purple, ~0.25 doublings) compared to at

saturation (red, ~1.4 doublings) and is accompanied by a larger relative spike

height.

1495

Figure 7: Temperature upshift response features are generally conserved across

microbes and can be captured by the TSEN model.

A) Growth-rate response to a temperature upshift on LB of laboratory-evolved *E.*

coli (light and dark blue, *n*=773–1279 cells) and natural isolates from various

hosts (orange to red, *n*=389–547 cells), *Escherichia fergusonii* (purple, *n*=997

cells), and *Bacillus subtilis* (green, *n*=236 cells). All upshifts were from 25 °C to

37 °C, except for *B. subtilis* (27 °C to 37 °C). Curves are mean growth rate and

shaded regions represent ±1 SEM.

B) Normalized growth rate followed a similar trajectory versus thermal time across

all strains/species for the data in (A).

C) A temperature upshift from 22 °C to 32 °C on the rich growth medium YE5S

caused the growth rate of the fission yeast *Schizosaccharomyces pombe* to

initially spike to close to the steady-state value at 32 °C, then decelerate to below

the steady-state value at 22 °C, then accelerate back to the new steady-state

value within less than a doubling (~100 min) (red, *n*=333 cells). Curves are mean

growth rate and shaded regions represent ±1 SEM.

D) A TSEN model with 5 intermediate reactions, each with a large (20 mM) and

highly temperature-sensitive K_M ($E_a^{(M)} = 22.5 \, \text{kcal/mol}$) produces similar

normalized growth rate dynamics with thermal time (black) as the *S. pombe* data

in (C) (red), characterized by a large spike, deceleration to <0, and fast recovery

within <1 doubling.

E) The TSEN model in (D), composed entirely of bottlenecks, predicts that a

temperature upshift results in a rapid, large decrease in the final intermediate

metabolite concentration (c_6), followed by a slower increase to the new steady-

state, which is lower than at lower temperature. All other metabolite

concentrations (c_{1-5}) increase monotonically toward their steady-state levels at

rates that depend inversely on their network depth (i.e., c_5 increases more slowly

than c_1).

F) An extended TSEN model with five intermediate reactions, each with a large (20

mM) and highly temperature-sensitive (E_a=22.5 kcal/mol) K_M, predicts a

temporary undershoot (black) upon a downshift to growth rates below the steady

state value at the lower temperature. The fission yeast *Schizosaccharomyces*

pombe exhibited an undershoot during a downshift from 32 °C to 32 °C on rich

medium (YE5S) (blue, *n*=54 cells) similar to model predictions. Experimental data

are the mean±1 SEM (shaded region) at each time point.

G) Asymmetry in growth-rate response to temperature up- and downshifts is caused

by the temperature sensitivity of K_M. If substrate concentration is near the K_M and

$E_a^{(M)} > 0$, an upshift causes a small initial increase in growth rate, followed by a

slow increase in substrate concentration to the new K_M via production (red).

Conversely, a downshift causes a comparatively larger initial decrease in growth

rate, followed by a slow decrease in substrate concentration to the new K_M via

dilution (blue).

H) Intracellular metabolite concentrations are generally much higher than the K_M of

their production enzyme for *E. coli* grown on glucose (data from Ref. [81]).

However, some metabolites have concentrations near or below the K_M of their

production, and potential bottlenecks (purple region, red points) are those with

$K_M > 1$ mM and substrate concentration $c < K_M$.

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