Signatures of innovation and selection in the extremotolerant yeast

Kluyveromyces marxianus

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Abstract

Organisms specialized to extreme environments can be the product of millions of years of evolutionary engineering and refinement. The underlying genetics can be quite distinct from the ones operating at earlier stages of trait innovation. In this work, we have developed the multi-stress resistant yeast *Kluyveromyces marxianus,* which diverged from its closest relative >20 million years ago, as a model for interspecies comparative biology and genomics. In growth assays of the *Kluyveromyces* genus, we found that *K. marxianus* exhibited unique tolerance of high heat and a subset of chemical stress conditions. We then generated and analyzed omic profiles from across the genus to find molecular features associated with—and potentially causal for—*K. marxianus* traits. Expression profiling revealed divergent lipid processing and membrane transport programs in *K. marxianus,* borne out in changes in lipid utilization in experimental assays. Sequence analyses found robust evidence for expansions in gene families in the *K. marxianus* genome, most notably among transmembrane transporters and in metabolic enzymes. In molecular-evolution tests, we identified adaptive protein variants throughout the *K. marxianus* genome among which plasma membrane transporters were over-represented. These data enable a model of the molecular mechanisms and evolutionary pressures underlying *K. marxianus* traits, including adaptive changes to transporters, lipid processing, and membrane functions mediating stress resistance.

Key Words

Significance statement

Many traits of basic and applied interest arose long ago and manifest in the modern day as fixed in a given species; understanding how evolution built them, potentially over millions of years, remains a key challenge in the field. In this study, we report stress-resistance phenotypes that distinguish the yeast *Kluyveromyces marxianus* from its relatives, and we discover unique patterns of genetic and regulatory variation in membrane-protein genes, as well as unique properties of lipid metabolism, in this species. We propose a broadly applicable model in which evolution can tune membrane lipid composition and membrane-protein function to boost cellular fitness in challenging environments.

Introduction

A central goal of evolutionary biology is to understand trait diversity in the natural world. In many cases, a phenotype of ecological or industrial interest defines a given eukaryotic species, distinguishing it from its relatives. Elucidating the genetic underpinnings of any such trait across species boundaries poses unique technical challenges. As a consequence, against a backdrop of landmark case studies mapping genotype to phenotype over deep trait divergences (Weiss and Brem 2019; Smith et al. 2020; Masly and Azom 2022), principles remain at a premium. What kinds of phenotypes tend to fix in species as they split from one another? What are the cellular mechanisms and the underlying genes and variants? Addressing these questions requires detailed study of ancient traits from physiology to the molecular level.

Single-celled fungi can serve as a powerful model system for evolutionary genetics (Hittinger et

al. 2015). *Kluyveromyces,* a genus of budding yeasts, are well-suited to this paradigm given

their ~25-million-year divergence (Shen et al. 2018) and wide-ranging ecology. *Kluyveromyces*

have been isolated from a range of terrestrial and aquatic environments (Anderson et al. 1986;

Nagahama et al. 1999; Am-In et al. 2008; Araujo and Hagler 2011; Suzuki et al. 2014; Cernak

et al. 2018; Williams et al. 2019; Chacón-Vargas et al. 2020; Al-Qaysi et al. 2021; Baptista et al.

2021; Avchar et al. 2022; Avchar et al. 2022; Spurley et al. 2022; Verma et al. 2023), but are

best known for roles in food and beverage fermentations (Kurtzman et al. 2011), including

elegant evolutionary analyses of the origin of lactases in dairy-associated lineages (Varela,

Puricelli, Ortiz-Merino, et al. 2019; Friedrich et al. 2023). An extensive literature has focused on

the growth of one species in the genus, *K. marxianus,* at temperatures exceeding 45°C,

motivated by applications in the bioproduction industry (Lane et al. 2011; Lertwattanasakul et al.

2013; Mejía-Barajas et al. 2017; Madeira-Jr and Gombert 2018; Fu et al. 2019; Hoshida et al.

2020; Wu et al. 2020; Kosaka et al. 2022; Flores-Cosío et al. 2024). The evolutionary driver for

the latter trait is unknown, though *K. marxianus* has been isolated from self-heating agricultural

and domestic compost (Suzuki et al. 2014; Avchar et al. 2022; Verma et al. 2023). Likewise,

cellular and genetic mechanisms underlying unique *K. marxianus* traits have remained

incompletely understood (Nespolo et al. 2020); potential clues have emerged from comparison

of this species to distantly related yeasts, including reports of resistance to chemical stress

(Saini et al. 2017; Linder 2018; Illarionov et al. 2021) and expansions in sugar and potassium

importer genes (Varela, Puricelli, Montini, et al. 2019; Papouskova et al. 2024).

We set out to use a comparative approach to trace in detail how *K. marxianus* diverged from its

relatives. We first catalogued stress resistance characters that distinguished *K. marxianus* from

the rest of the species of its clade. We then applied omic profiling to find unique expression

programs and genomic features in *K. marxianus*. The results provided insights into the

underpinnings and the evolution of the *K. marxianus* trait syndrome.

Results

***K. marxianus* exhibits a stress resistance syndrome unique in its genus**

With the ultimate goal of understanding evolutionary innovations in *Kluyveromyces*, we first

sought to survey stress resistance traits across the genus. We profiled the growth in liquid

culture of four species associated with terrestrial habitats (*K. marxianus, K. lactis, K.*

wickerhamii, and *K. dobzhanskii*) and three aquatic species (*K. aestuarii*, *K. siamensis*, and *K.*

nonfermentans) in a panel of media conditions (Figure 1 and Table S1). At 42°C, *K. marxianus*

grew far better than its relatives, to an extent beyond the pattern in a permissive control

condition (rich medium at 28°C; Figure 1A); genetically distinct *K. marxianus* isolates from

various substrates and geographical origins phenocopied each other with respect to high-

temperature growth except for one thermosensitive strain isolated from a fly (Figure S2, Table

S1), as expected if loss of thermotolerance were a rare and recent event in this predominantly

thermotolerant species (Lane et al. 2011). In ethanol, caffeine, the DNA intercalator propidium

iodide, and the DNA damage agent methyl methanesulfonate (MMS), *K. marxianus* likewise

outperformed the other species of the genus (Figure 1A). Our profiling also identified other

conditions in which *K. marxianus* did not stand out with respect to growth (Figure S1B). We

conclude that *K. marxianus* is unique in the genus for its resistance to a broad subset of abiotic

challenges, including high temperature.

The uniqueness of *K. marxianus* resistance phenotypes depends on growth phase

For many microbes, when cells face nutrient exhaustion, they shut down exponential (log-

phase) growth and enter the quiescent, extra-durable state called stationary phase. The

difference between *K. marxianus* and its relatives in stress resistance that we had noted across

a growth timecourse (Figure 1A) might also manifest in the stationary state or, alternatively, its

cellular mechanism could be tied to active cell division. To distinguish between these

possibilities, we focused on thermotolerance as a test case. We used a viability assay in which

we inoculated a given liquid culture into rich medium; incubated for growth at the permissive

temperature until nutrient exhaustion; subjected this stationary-phase culture to a short heat

shock; and used it to seed colonies for growth at the permissive temperature on solid medium

(Figure 1B). Results revealed only modest differences between species in heat shock

resistance under this stationary-phase heat treatment, with no particular advantage for *K.*

marxianus (Figure 1B). By contrast, when we treated exponential-phase cultures with heat

shock, *K. marxianus* exhibited much higher viability than did the other species of the genus

(Figure 1C), paralleling its advantage during chronic high-temperature exposure (Figure 1A). No

such differences were apparent in a permissive 28°C control experiment (Figure S3B). We

conclude that for high temperature, the *K. marxianus* advantage only manifests when cells are

actively dividing, and that cell death, rather than slow or arrested growth, mediates the defects

of the rest of the genus.

To extend our analysis of cell death as the underlying cellular basis of species differences in

stress, we next assayed viability in exponential-phase cultures across a panel of representative

stresses, focusing on the stress-sensitive species *K. lactis* as a point of comparison for *K.*

marxianus (Figure S1A). The latter exhibited a survival advantage in all stress conditions tested

(Figure S4). The difference was amplified by oxygen depletion, though both species performed

better in normoxia (Figure S4), as expected (Lertwattanasakul et al. 2013; Mejía-Barajas et al.

2017; Madeira-Jr and Gombert 2018; Fu et al. 2019; Hoshida et al. 2020; Kosaka et al. 2022).

Together, these trends from assays of viability establish the resistance character of *K.*

marxianus as a lineage-unique gain of protection against lethal failures of the proliferation

program under temperature and chemical stress.

Unique expression and lipid utilization programs in *K. marxianus*

To learn more about the underpinnings of divergence across *Kluyveromyces*, we turned to an

expression profiling approach, for which we again chose *K. lactis* as a representative stress-

sensitive species for comparison against *K. marxianus*. We surveyed the transcriptomes of the

two species under exponential growth in representative treatments where we had observed

divergent growth phenotypes—high temperature, caffeine, MMS, and ethanol—and in the

permissive control of rich medium at 28°C, with stress conditions chosen to enable growth of

both species (Table S2 and see Methods). Principal component analyses of normalized RNA-

seq read counts made clear that the major source of variation across the data set was a marked

difference between *K. lactis* and *K. marxianus* transcriptomes in all conditions, including

controls (Figure 2A, Figure S5, and Table S2). Functional-enrichment tests revealed induction

of membrane-lipid trafficking and intracellular transport, clathrin endocytosis, and cell wall genes

driving the values of the major principal component in *K. marxianus* transcriptomes (Figure 2B

and Table S2). High expression of translation and ribosomal RNA processing genes drove the

values of the major principal component in *K. lactis* samples (Figure S5 and Table S2). Apart

from these effects, the second principal component reflected a suite of genes that *K. lactis*

turned up and down depending on treatment, whereas the *K. marxianus* transcriptome was

much less volatile with respect to stress (Figure 2A, Figure S5, and Table S2), as expected if *K.*

lactis underwent more functional failures during growth in our panel of conditions. Most salient

in the set of stress-responsive genes in *K. lactis* was heightened induction of translation gene

sets over and above the effect we had noted in control conditions (Figure 2C, Figure S5, and

Table S2), dovetailing with previous studies (Lertwattanasakul et al. 2015). Functional-genomic

enrichment analysis of raw expression measurements yielded similar trends (Table S3).

Our observations of divergent expression of membrane-lipid trafficking genes in *K. marxianus*

(Figure 2B and Table S2) echoed previous comparative-biology studies of an unusual inability

by *K. marxianus* to take up sterol from growth medium (Dekker et al. 2021) and unusual effects

of sterol-metabolism mutations (Ren et al. 2024). We hypothesized that *K. marxianus* could

likewise exhibit divergent phenotypic responses to other classes of lipid. To explore this notion,

we used an experimental paradigm testing utilization by yeast of exogenous lipids when *de*

novo fatty acid synthesis is blocked by the drug cerulenin (Jung et al. 2013). Using oleate as the

lipid supplied in the medium in this assay, we found *K. marxianus* to be among the lowest

performers of the genus (Figure S6), a surprising contrast to its advantages in stress conditions

(Figure 1A). This minimal exogenous oleate processing by *K. marxianus*, even when it was

required for optimal growth, paralleled the behavior of *K. marxianus* in sterols (Dekker et al.

2021), suggestive of a hard-wired preference by this species for internal lipid sources.

Interestingly, the aquatic species *K. siamensis* and *K. nonfermentans* also failed to utilize

exogenous oleate in our assays (Figure S6), plausibly as a product of independent evolutionary

losses in their niche.

Unique transporter and metabolic gene duplications in the *K. marxianus* genome

We reasoned that genomic features distinguishing *K. marxianus* from its relatives could serve

as a source for clues to the underlying molecular basis of its traits. As a first strategy to find

genomic novelties in *K. marxianus*, we focused on species-specific copy number change in

paralogous gene families. From annotated reference genomes for six *Kluyveromyces* species

(*K. marxianus, K. lactis, K. wickerhamii, K. dobzhanskii*, *K. aestuarii*, and *K. nonfermentans*;

Figure S1A), plus outgroups from nearby clades in the Saccharomycotina subphylum (including

S. cerevisiae and *C. albicans* as well-annotated model organisms), we identified rapidly

changing gene families in each branch with tools of the CAFE 5 package (Mendes et al. 2021).

This approach identified 16 gene families with inferred gain or loss events along the *K.*

marxianus lineage at rates that were unusual relative to the average across the species set

(Figure 3A and Table S4), including families subject to tandem duplications and those with

genes across the *K. marxianus* chromosomes (Figure 3B and Table S4). Of these, 13 were

families with expansions in *K. marxianus* that could be classified based on domain annotations

as functioning in metabolism or localized to the plasma membrane, the latter including

transporters annotated as nutrient importers and xenobiotic efflux pumps (Figure 3A). These

data make clear that gene family expansions are prevalent in the *K. marxianus* genome, and

they highlight membrane proteins and metabolism as compelling candidate molecular players

underlying *K. marxianus* phenotypes.

Widespread phylogenetic evidence for positive selection on amino acid alleles in *K.*

marxianus

As a further means to identify genomic correlates of *K. marxianus* phenotypes, we pursued

molecular-evolution analyses of amino acid variation on a per-gene basis. We reasoned that

some phenotypes unique to *K. marxianus* could have evolved as a product of adaptation to

challenging ecological niches, and that at relevant loci, we could detect evidence for positive

selection on protein-coding sequences. For a phylogenetic test toward this end, at each gene in

turn, we aligned one-to-one orthologs from reference genomes for our six focal *Kluyveromyces*

species, to which we fit models in the PAML (Yang 2007) and HyPhy (Pond et al. 2005)

packages earmarking codons subject to positive selection along the *K. marxianus* lineage.

Emerging from these tests were >500 and 80 genes with evidence for positive selection from

PAML and HyPhy analyses, respectively (Figure 4A-B), overlapping in 51 cases (Figure 4B and

Table S5). We considered the latter genes, given their signal in multiple independent analysis

frameworks, as representing the strongest cases for positive selection in *K. marxianus*

according to phylogenetics. This hit list included the potassium transporter *TRK1*, whose *K.*

marxianus ortholog is known to be hyperactive relative to that of model yeast (Papouskova et al.

2024), and other genes annotated in transmembrane transport as well as metabolism, cell wall

structure, and protein production (Figure 4B and Table S5). Control analyses revealed far less

signal for positive selection on the lineage leading to *K. lactis* (Figure 4A and Table S5),

supporting the inference of a history of particularly pervasive adaptation at the amino acid level

in *K. marxianus*.

For most of the many gene hits from our phylogenetic tests focused on *K. marxianus*, a small

number of codons per gene were classified as targets of positive selection (Table S5). We

expected that if the derived alleles at each such site had undergone a selective sweep through

K. marxianus populations, we could detect it across strains of this species. To test this, we

carried out short-read resequencing of the genomes of five wild *K. marxianus* isolates (Table

S1) and used the resulting reads alongside our reference genome of the Km31 *K. marxianus*

strain as input to a pipeline for variant calling, pseudogenome construction, and sequence

alignment. We then inspected these alignments at each site where the *K. marxianus* allele had

been flagged as arising under selection according to our phylogenetic analysis of reference

genomes. At 99% of the latter, we detected complete conservation across *K. marxianus* strains

(Figure 4C and Table S5). These data establish that alleles in Km31 are representative of the

population more broadly at these loci, providing further support for our inference of their derived

alleles maintained under selection.

Enrichment for amino acid variation between *Kluyveromyces* species in transporter

genes

To complement our phylogenetic analyses, we next applied population-based molecular-

evolution tests that used our *K. marxianus* resequencing data and a population-genomic

resource for *K. lactis* (Friedrich et al. 2023). We implemented McDonald-Kreitman molecular

evolution paradigms (McDonald and Kreitman 1991) to assess evidence for differences in

selective pressure between the species on a given protein sequence, as follows. For each

coding region we tabulated sites of non-synonymous and synonymous divergence between *K.*

marxianus and *K. lactis*, and likewise for polymorphic variants within the species (Table S6).

Using these counts in a non-polarized McDonald-Kreitman test on a per-gene basis, we

identified 11 genes with a significant excess of interspecies amino acid divergence across the

coding region (relative to polymorphism and for synonymous variation; Figure 4D and Table

S6). Thus, relative to our phylogenetic methods (Figure 4A), the McDonald-Kreitman scheme

was under-powered in this system, as expected if most loci only had a few amino acid targets of

adaptation between *K. marxianus* and *K. lactis* (Table S5). But among the gene hits that did

emerge from the McDonald-Kreitman test, each represented an inference of positive selection

from population data that complemented our phylogenetic results. Two such loci had also been

top-scoring in both of our phylogenetic frameworks, the annotated glycolytic enzyme gene *FBA1*

and *FAT3,* annotated in lipid transport (Figure 4C-D). Allele-swap experiments revealed a small

(1.09-fold) but significant advantage accruing from the *K. lactis* allele of *FAT3* in the *K.*

marxianus background in assays of lipid utilization, consonant with the better performance by

wild-type *K. lactis* in the latter (Figure 4E and Figure S6); no such allele-swap effect was

detectable in standard-media controls (Figure S7). This result validated our inference from

sequence analyses (Figure 4C-D) of differential function of *FAT3* between the species, and

attested to a modifying role for *FAT3* in a complex genetic architecture of lipid processing

preferences.

For more holistic insights into *Kluyveromyces* evolution using our population-genomic data

resource, we developed a group-wise version of the McDonald-Kreitman paradigm, in which we

tabulated the neutrality index (NI) for a given gene as non-synonymous divergence normalized

for polymorphism and for synonymous variation, and we evaluated significance of this metric

across cohorts of genes of similar function via resampling (Figure 4F and Table S7). For

metabolic gene groups with extreme NIs in this test, focused analyses indicated that the signal

was driven by low rates of protein evolution within species, reflecting a history of purifying

selection (Table S7). By contrast, for five Gene Ontology terms, the individual components of

the NI metric followed the opposite pattern: non-synonymous variation between species was

high in the genes of the group and polymorphism levels were on par with the genomic average

(Figure 4E and Table S7). Of particular note among these gene groups enriched for low NI was

a transmembrane transport gene cohort (Figure 4F), echoing our observation of membrane

protein gene family expansions in *K. marxianus* (Figure 3) and the annotated transporters,

including *TRK1* and *FAT3*, that had been top-scoring in our single-gene phylogenetic and

McDonald-Kreitman analyses (Figure 4D and Table S5). Taken together, our molecular-

evolution analyses attest to a complex history of selection on loci throughout the *K. marxianus*

genome, with strong concordance across our test approaches for evidence for unique selective

pressures on the coding regions of transporter genes.

Discussion

Against the backdrop of years of work mapping the genetic basis of trait variation within fungal

species (Liti and Louis 2012; Taylor et al. 2017), dissecting fixed trait divergences between

species remains a key challenge for mycologists. In landmark cases, individual loci have been

identified that underlie such lineage-defining phenotypes in fungi (Nagy et al. 2017; Wang et al.

2024). For the vast majority of traits varying across fungal species barriers, however, the

mechanistic underpinnings remain unknown. In this work, we have established a framework for

discovery of candidate genes and pathways underlying traits unique to *K. marxianus*. Our

results have revealed attributes that distinguish *K. marxianus* from the rest of its genus: stress

resistance in growth assays, divergent expression programs and lipid processing phenotypes,

and sequence evidence for gene-content and amino-acid variation. These observations serve to

complement classic trait compendia (Kurtzman et al. 2011) and the modern literature (Lane and

Morrissey 2010; Lane et al. 2011; Madeira-Jr and Gombert 2018). In terms of genetics, the

alleles we have found to be unique in *K. marxianus* represent candidates for the determinants

that nature would have used to build the trait syndrome in this species. We expect that as these

loci are validated, they will prove sufficient to reconstitute traits from *K. marxianus* in an

exogenous background, as opposed to the handful of previous studies that have reported genes

necessary for thermotolerance in *K. marxianus* (Falcão Moreira et al. 1998; Wu et al. 2020;

Montini et al. 2022).

Most pervasive in our omic profiles was the trend of induction of membrane-gene expression,

expanded membrane-gene families, and derived amino acid alleles in single-copy transporter

genes, in the *K. marxianus* genome relative to the rest of its clade. The latter include gains by *K.*

marxianus in sugar and potassium transporter repertoires, which were previously analyzed in

comparisons with distant fungal relatives (Varela, Puricelli, Montini, et al. 2019; Papouskova et

al. 2024) and which we can now date to the divergence of *K. marxianus* from its sister species.

A causal phenotypic role of this remodeling of the transporter repertoire in the stress resistance

by *K. marxianus* remains to be established. It is tempting to speculate that *K. marxianus* has

tuned many of its transporters to tighten selectivity against extracellular toxins or to improve

function in the face of heat or chemical stress. Additionally, given the evidence from our work

and that of others (Dekker et al. 2021) for heightened membrane trafficking and limited

exogenous lipid usage in *K. marxianus*, we propose that evolution has tuned intracellular lipid

processing in this species, with molecular mechanisms to restrict exogenous uptake that involve

FAT3. Future analyses will be necessary to test directly for a relationship between lipid

processing changes and stress resistance in *K. marxianus*, potentially including specialized

programs to tune membrane fluidity as seen in other yeast systems (Henderson and Block

2014; Lairón-Peris et al. 2021; Ribeiro et al. 2022; Sokolov et al. 2022). Any such unique

attributes of *K. marxianus* membrane lipids could be interconnected with the genetic and

expression changes we have observed at transporter genes, *e.g.* to adjust protein anchoring or

to compensate for changes to membrane barrier function that would impact passive nutrient

acquisition (Ferenci 2016). That said, we observed signals of evolutionary innovation by *K.*

marxianus in genes of many other functions, and globally, we picture a multifaceted molecular

mechanism for its resistance traits.

Why, ecologically, would *K. marxianus* have evolved stress tolerance? The ecological pressures

that would have driven changes in this lineage remain poorly established. Though well-

recognized as an industrial dairy yeast (Prado et al. 2015; Gethins et al. 2016; Ortiz-Merino et

al. 2018; Varela, Puricelli, Ortiz-Merino, et al. 2019; Yazdi et al. 2022), *K. marxianus* was likely

domesticated for this purpose fairly recently, as inferred for *K. lactis* (Friedrich et al. 2023). And

though *K. marxianus* can also be isolated from rotting fruit (Williams et al. 2019; Al-Qaysi et al.

2021), it may not have specialized narrowly to such substrates: a neighboring clade that

includes *Saccharomyces cerevisiae* produces more ethanol than do any of the *Kluyveromyces*

species (Nespolo et al. 2020), suggesting a weaker drive in the latter toward this putative

strategy to kill off microbial competitors in high-sugar environments. Among microbial-ecology

findings, the strongest clue to the origin of unique phenotypes in *K. marxianus* lies in its

prevalence in decomposing plant material other than fruit, including leaf litter and pine needles

(Spurley et al. 2022), cow dung (Avchar et al. 2022), industrially processed cocoa beans

(Baptista et al. 2021), agave (Chacón-Vargas et al. 2020), and sugar cane (Anderson et al.

1986; Cernak et al. 2018) as well as industrial and domestic compost (Suzuki et al. 2014;

Avchar et al. 2022; Verma et al. 2023). Plant defense compounds in decomposing material are

a compelling candidate driver for the rise of resistance traits in *K. marxianus* (Baptista and

Domingues 2022) since they can persist for days in a leaf or stem after abscission (Burton

1982; Goodspeed et al. 2013; Shimada et al. 2015). Furthermore, some evidence for low pH

deep in compost piles (Rainey and Covey 2016) suggests that this condition could also have

contributed to *K. marxianus* evolution. In this scenario, the phenotypic syndrome of *K.*

marxianus would involve not only resistance to the stresses of the decaying plant environment,

but also the rapid utilization of simple sugars liberated early in plant breakdown, mediated by

the new copies and new alleles of metabolic genes we have noted in the *K. marxianus* genome.

As *K. marxianus* lacks the capacity to degrade lignocellulosic plant cell walls, these would be

left to other fungal saprotrophs acting later in decomposition.

We thus envision an ecological model in which *K. marxianus* originally evolved as a plant decay

specialist, with extant strains coming to occupy a broad range of niches, including soil and

human and animal material (Rij 2013; Ortiz-Merino et al. 2018; Zhang et al. 2021). Given that

we and others have seen conservation of resistance traits across *K. marxianus* strains (Lane et

al. 2011; Madeira-Jr and Gombert 2018; Lappe-Oliveras et al. 2023), we infer that unique

capacities arose early in *K. marxianus,* sometime after *K. marxianus* originated as a species,

~25 million years ago (Shen et al. 2018), and persisted during its radiation into modern

populations.

Methods

1. Strains

Strains used in phenotyping experiments, population-genomic analyses, and mutant

phenotyping are listed in Table S1.

2. Liquid growth phenotyping of wild-type *Kluyveromyces*

Liquid culture experiments in stress and standard-condition controls in Figure 1A used *K.*

marxianus Km31 (Cernak et al. 2018); *K. lactis* yLB72 (Sorrells et al. 2015); and the strains of

K. dobzhanskii, K. wickerhamii, K. nonfermentans, K. aestuarii, and *K. siamensis* listed in Table

S1. For a given species and condition, we streaked a frozen stock onto yeast peptone dextrose

(YPD) agar plates, incubated for two days at 28°C, picked a single colony, inoculated into 5 mL

liquid YPD, and incubated with shaking at 28°C for 16-18 hours. We call this the first pre-

culture. We diluted, into fresh liquid YPD, an inoculum of the first pre-culture at the volume

required to attain an optical density (OD_{600}) of 0.05 for a total culture volume of 5 mL, and we

incubated this second pre-culture with shaking at 28°C for ~7 hours until it reached $OD_{600} = 0.2$.

For unstressed controls in Figure 1A, we diluted an inoculum of the second pre-culture into

fresh liquid YPD at the volume required to attain $OD_{600} = 0.2$ for a total culture volume of 5 mL.

150 μL of this experimental culture was transferred to each of 12 wells of a 96-well plate, sealed

with a Breathe-Easy membrane (Diversified Biotech), for incubation at 28°C and growth

measurements across a 24-hour timecourse in a Tecan M200 PRO plate reader (parameter

time point measurement, OD_{595}). For heat stress treatment in Figure 1A, setup and growth

assays were as above except that incubation of the experimental culture was at 42°C. For

chemical stress treatments in Figure 1A, setup and growth assays were as above except that

for the experimental culture, before transfer to the 96-well plate, ethanol (Koptec) was added to

attain a concentration of 6.5% (v/v); caffeine (Sigma-Aldrich) was added to attain 25 mM;

methane methylsulfonate (MMS; Thermo Scientific) was added to attain 0.03% (v/v); or

propidium iodide was added to attain 1mM, and growth timecourses were 48 to 72 hours. For

chemical stress treatments and growth measurements in Figures S1 and S2, for a given

species and condition, streaking and the first pre-culture were as above. We diluted an

inoculum of the first pre-culture into fresh liquid YPD at the volume required to attain $OD_{600} = 0.2$

for a total culture volume of 5 mL, with 1 M NaCl (Fisher), 3% glycerol (v/v; Fisher), 80 mM

$CaCl_2$ (Sigma), 250 mM rapamycin (Research Products International), 6 mM H_2O_2 (Fisher), or

16% (v/v) Triton X-100 (Fisher), followed by incubation and growth measurements in the 96-well

format as above.

3. Assays of cell survival from *K. marxianus* and *K. lactis* stationary and log-phase liquid culture

For survival assays of cells in exponential phase in Figures 1B,C and S3, for *K. marxianus* Km31 and separately for *K. lactis* yLB72 we streaked a frozen stock onto yeast peptone dextrose (YPD) agar plates, incubated for two days at 28°C, picked a single colony, inoculated into 5 mL liquid YPD, and incubated with shaking at 28°C for 16-18 hours. We diluted, into fresh liquid YPD, an inoculum of this first pre-culture at the volume required to attain $OD_{600} = 0.05$ for a total culture volume of 5 mL, and we incubated this second pre-culture with shaking at 28°C for ~7 hours until it reached $OD_{600} = 0.2$. We took this second pre-culture directly into experimental treatment as follows. For unstressed controls, serial dilutions of the culture were spotted onto agar plates and incubated for 2 days at 28°C. For heat shock, 1 mL of the culture was incubated in a heat block at 47°C for 30 minutes and then transferred to ice for 2 minutes, followed by spotting and incubation as above.

For survival assays of cells in stationary phase in Figures 1B and S3, for *K. marxianus* Km31 and separately for *K. lactis* yLB72 we streaked a frozen stock onto yeast peptone dextrose (YPD) agar plates, incubated for two days at 28°C, picked a single colony, inoculated into 5 mL liquid YPD, and incubated with shaking at 28°C for 96 hours. Heat shock and spotting (and unstressed controls) were as above.

4. Assays of cell survival from *K. marxianus* and *K. lactis* anaerobic and aerobic liquid cultures

As *Kluyveromyces* cannot tolerate strictly anaerobic conditions (Kiers et al. 1998; Ishtar Snoek

and Yde Steensma 2006; Merico et al. 2007; Dekker et al. 2021), for Figure S4 we used a

limited-oxygen experimental paradigm (Hoshida et al. 2020) as follows. For *K. marxianus* Km31

and separately for *K. lactis* yLB72, for each treatment we isolated a single colony on solid plates

and carried out first and second pre-cultures in liquid YPD at 28°C under aerobic conditions as

in Section 2. For unstressed controls in anaerobic conditions, we diluted an inoculum of the

second pre-culture into fresh liquid YPD at the volume required to attain $OD_{600} = 0.05$ for a total

culture volume of 5 mL. 150 μL of this experimental culture was transferred to each of 12 wells

of a 96-well plate, which was placed (with lid) into an AnaeroPouch (ThermoScientific) with a

AnaeroPouch - Anaero gas pack. The sealed pouch and plate were incubated for 72 hours at

28°C. Then we collected 30 μL of culture from each well and combined them all into one master

culture, 100 μL of which we serially diluted into spots on agar plates, followed by incubation for

2 days at 28°C. Aerobic controls were treated analogously except that the 96-well plate was

inoculated without a pouch. Viability assays of chemically stressed cells in anaerobic conditions

and aerobic controls were as above except that for the experimental culture, before transfer to

the 96-well plate, ethanol, caffeine, or MMS were added as in Section 2. Viability assays of

heat-treated cells in anaerobic conditions and aerobic controls were as above except that the

sealed pouch and plate were incubated for 24 hours at 39°C.

5. Transcriptional profiling

5.1. Culture protocol and experimental design.

For a given replicate of RNA-seq of *K. marxianus* Km31 and separately for *K. lactis* yLB72 in

unstressed control conditions, we isolated a single colony on solid plates and carried out first

and second pre-cultures in liquid YPD at 28°C as in Section 2. For unstressed controls, we

diluted an inoculum of the second pre-culture into fresh liquid YPD at the volume required to

attain $OD_{600} = 0.05$ for a total culture volume of 50 mL. This experimental culture was incubated

at 28°C with shaking until it reached $OD_{600} = 0.4\text{-}0.85$. From this culture we took an aliquot

whose volume contained 2 OD units of cells, pelleted its cells by centrifugation for 5 minutes at

1,500 x g, and resuspended in 1 mL of RNAlater (ThermoFisher) followed by storage at 4°C for

up to 48 hours. For RNA-seq of heat-stressed cells, culture, pelleting, and storage were as

above except that the experimental culture was incubated at 39°C; for RNA-seq of cells under

chemical stress, culture, pelleting, and storage were as above except that the experimental

culture was done in YPD with 22 mM caffeine, 0.01% MMS, or 3% ethanol. In each case, we

used incubation times for the respective condition and species that allowed the culture to reach

the target optical density (*i.e.* mid-exponential phase). For expression-based reannotation of *K.*

marxianus Km31 and *K. lactis* yLB72 (see below), we used the above pipeline for a preliminary

expression profiling experiment which we call the training batch: we cultured one biological

replicate of Km31 and yLB72 at 37°C and one of Km31 and yLB72 in unstressed control

conditions. For comprehensive transcriptional profiling analyses in Figure 2 and Figure S5, we

used the above pipeline to generate cell pellets in two production batches. In one batch we

grew three biological replicates of Km31 and three of yLB72 in 39°C heat stress, and three

unstressed cultures of each species. In another batch we grew three biological replicates of

each species in caffeine, three in MMS, and three in ethanol, and three unstressed controls.

5.2. RNA isolation and sequencing.

For RNA isolation of a given sample pellet stored in RNAlater (see Section 5.1), we centrifuged

for 5 minutes at 1,500 x g, and after decanting of the supernatant, we resuspended the pellet in

200 *µ*L of nuclease-free water followed by addition of 750 *µ*L of BashingBead buffer from the

Direct-Zol RNA MicroPrep RNA kit (Zymo Research). We then transferred our 950 *µ*L of

suspension into BashingBead tubes, vortexed for 20 minutes, and centrifuged for 5 minutes at

12,000 x g. We took ~600 *µ*L of supernatant from the top layer being careful not to touch the

pellet, transferred to a new tube, and mixed with an equal volume of 100% ethanol. This mixture

was used as input to the rest of the kit, following the manufacturer's instructions. RNA library

preparation and sequencing of ~20M 150 bp paired-end reads per sample was carried out by

Novogene, Inc.

5.3. Genome re-annotation and ortholog calls for K. marxianus *and* K. lactis

To generate a reference genome for *K. marxianus* strain Km31, we proceeded as follows. We

first used bwa (bio-bwa.sourceforge.net) to map the RNA-seq reads from the *K. marxianus*

cultures of the training batch of our transcriptional profiling (see Section 5.1) to a published

genome of the DMB1 strain of *K. marxianus* (Suzuki et al. 2014). We then used these

mappings, requiring mapping qualities of >20 and mapped lengths >20, to call single-nucleotide

polymorphisms with BCFtools (Li 2011; Danecek et al. 2021) mpileup with the -I flag to ignore

indels, and filtering for exclusion of variants with: a depth of less than 10 reads, or more than

10% of reads with a mapping quality of 0 supporting the variant. At the called polymorphisms,

we computationally introduced Km31 alleles into the DMB1 genome sequence with the

consensus tool in BCFTools to generate a first-pass pseudogenome for Km31. Next, we used

this pseudogenome and the training batch RNA-seq reads as input into transcript assembly with

Trinity (Grabherr et al. 2011) and annotation with PASA (Haas et al. 2003), and we took the

output as our final annotated genome for *K. marxianus* Km31 (Supplementary Data 1). We

generated a reference genome for *K. lactis* strain yLB72 as above, except that we used RNA-

seq from the *K. lactis* training batch and the published genome of *K. lactis* strain NRRL Y-1140

(Dujon et al. 2004) (Supplementary Data 1). To call orthologous gene pairs between *K.*

marxianus Km31 and *K. lactis* yLB72, we used our final annotations from the two species as

input into OrthoFinder (Emms and Kelly 2019). We retained all one-to-one orthology calls, *i.e.*

cases in which a single annotated gene from *K. marxianus* was called orthologous to a single

gene from *K. lactis*. We also sought to valorize cases in which OrthoFinder, with the goal of

finding orthologs in species B of a gene $G_{1,A}$ in species A, did not distinguish between n

candidate orthologous genes $G_{1...n,B}$ from species B. We evaluated each candidate $G_{i,B}$ for

synteny: if the next gene up- or downstream of $G_{i,B}$ in the species B genome was called a one-

to-one ortholog of the up- or downstream genes of $G_{1,A}$ in the species A genome, we retained

this case as a bona fide ortholog pair. Our final set comprised 3578 ortholog pairs between *K.*

marxianus Km31 and *K. lactis* yLB72. *Saccharomyces* orthologs were taken from (Sorrells et al.

2018).

5.4. Production-batch transcriptional profiling data analysis

For comprehensive transcriptional profiling analyses in Figure 2 and Figure S5, we used our

RNA-seq data from cultures of *K. marxianus* Km31 and *K. lactis* yLB72 from production batches

(see Section 5.1) as follows. For the RNA-seq reads from a given replicate of a given species

(*K. marxianus* or *K. lactis*) and condition (39°C, ethanol, caffeine, MMS, or unstressed control),

we mapped to the respective pseudogenome (see Section 5.3) using the TopHat (Kim et al.

2013) aligner with default parameters, and we used these mappings as input into HTseq

(Anders et al. 2015) to generate raw read counts per gene. For a given species and stress, we

used the counts from all replicates from the stress, and the unstressed control from the

respective batch, as input into edgeR (Robinson et al. 2010) to generate normalized counts per

gene and replicate and a normalized log$_2$ fold-change between stress and control conditions as

an average across replicates. Principal component analysis (PCA) of the RNA-seq data was

done using the PCA module of scikit-learn (Pedregosa et al. 2011). The edgeR normalized

counts for each gene in each treatment were scaled to unit variance with scikit-learn before

running the PCA. Principal component weights are listed in Supplementary Table 2.

To identify Gene Ontology (GO) terms associated with principal components, we assigned GO

annotations to each gene using the *K. lactis* annotation from FungiDB

(https://fungidb.org/fungidb/app/record/dataset/NCBITAXON_284590). For each GO term with

at least three annotated genes in our dataset, we tested whether genes within that term had

significantly extreme PC1 or PC2 weights compared to the null expectation. We used a

bootstrap resampling approach to generate the null distribution: for each GO term containing n

genes, we randomly sampled n genes (with replacement) from the complete set of genes and

calculated the mean PC weight of this random sample. This process was repeated 10,000 times

to construct an empirical null distribution representing the expected mean PC weight for a

random gene set of that size. We calculated two-tailed *p*-values by comparing the observed

mean PC weight to this null distribution. To correct for multiple testing across all GO terms, we

applied the Benjamini-Hochberg false discovery rate (FDR) correction using the multipletests

function from statsmodels (Seabold and Perktold 2010), with a significance threshold of α =

0.05.

To identify gene groups in which a given stress treatment evoked significant gene induction or

repression relative to the unstressed control, in *K. marxianus* Km31 and separately in *K. lactis*

yLB72 (Table S3), we carried out resampling-based enrichment tests as follows. We used

assignments of each gene to Gene Ontology terms for *K. lactis* from FungiDB

(https://fungidb.org/fungidb/app/record/dataset/NCBITAXON_284590), and we propagated

these assignments to orthologous genes in *K. marxianus* from Section 5.3. For a given species

and stress, for each Gene Ontology term in turn, for the *n* genes from the term with expression

observations, if $n > 5$ we collated the genes' $\log_2$ fold-changes in expression between stress

and the untreated control, each of which was a mean across replicates (from edgeR; see

above). We took the mean of these fold-changes across the genes of the term, m_{true}. We then

picked *n* random genes from the genome and tabulated their mean expression fold-change for

the respective species and stress, $m_{resample}$. Repeating the latter resampling 1000 times, we

calculated an empirical *p*-value reporting the enrichment of the magnitude of expression fold-

change as the percentage of resamples for which ($|m_{resample}| \geq (|m_{true}|)$. We used the *p*-values for

all terms tested for the respective species and stress as input into multiple testing correction

with the Benjamini-Hochberg method.

6. Molecular-evolution analyses

6.1. Gene duplication analysis

As input to the gene family copy number analysis for Figure 3 and Table S4, genomes and

annotations were as follows. For *K. marxianus* and *K. lactis* we used the reference genomes

and annotations of Km31 and yLB72, respectively, from Section 5.3. For *K. wickerhamii* we

used the reference genome and annotation of UCD54-210 from (Sorrells et al. 2018). For the *K.*

nonfermentans strain NRRL Y-27343 (GenBank acc. no. GCA_030569915.1), the *K. aestuarii*

strain NRRL YB-4510 (GenBank acc. no. GCA_003707555.2), the *K. siamensis* strain CBS

10860 (GenBank acc. no. GCA_030579315.1), and the *K. dobzhanskii* strain NRRL Y-1974

(GenBank acc. no. GCA_003705805.3) we used YGAP (Proux-Wéra et al. 2012) to generate *de*

novo annotations from previously generated reference genomes (Supplementary Data 1). As

outgroup species we used the genomes and annotations for *Ashbya aceri* (GenBank acc. no.

GCA_000412225.2), *Candida albicans* (GenBank acc. no. GCA_000182965.3), *Eremothecium*

cymbalariae (GenBank acc. no. GCA_000235365.1), *Eremothecium gossypii* (GenBank acc.

no. GCA_000091025.4), *Eremothecium sinecaudum* (GenBank acc. no. GCA_001548555.1),

Lachancea dasiensis (GenBank acc. no. GCA_900074725.1), *Lachancea fantastica* (GenBank

acc. no. GCA_900074735.1), *Lachancea fermentatii* (GenBank acc. no. GCA_900074765.1),

Lachancea lanzarotensis (GenBank acc. no. GCA_000938715.1), *Lachancea meyersii*

(GenBank acc. no. GCA_900074715.1), *Lachancea mirantina* (GenBank acc. no.

GCA_900074745.1), *Lachancea nothofagi* (GenBank acc. no. GCA_900074755.1), *Lachancea*

quebecensis (GenBank acc. no. GCA_002900925.1), *Lachancea thermotolerans* (GenBank

acc. no. GCA_000142805.1), and *Saccharomyces cerevisiae* (GenBank acc. no.

GCA_000146045.2). We used proteomes for each species as input into OrthoFinder (Emms

and Kelly 2019) to find groups of orthologs. We then used the time-weighted tree and gene

family counts from OthoFinder as input into CAFE 5 (Mendes et al. 2021) to analyze gene

family contractions and expansions. Gene families that did not exist at the root were included.

We adjusted *p*-values with the Benjamini-Hochberg test to correct for multiple testing. We used

CafePlotter (https://github.com/moshi4/CafePlotter) to visualize significant gene family

expansions and contractions on the phylogenetic tree. We then assigned functions for each

gene family by running all proteins from all species for each gene family through InterProScan

(Jones et al. 2014). We took the most common InterPro term in the output of the scan as the

inferred function of the gene family in Figure 3.

6.2. Phylogenetic analyses

As input to phylogenetic analyses of one strain for each *Kluyveromyces* species for Figure 4

and Table S5, we used genomes and annotations for the *Kluyveromyces* genus excluding *K.*

siamensis as in Section 7.1. We called orthologs across these six species with OrthoFinder

(Emms and Kelly 2019), and for a given orthogroup we generated protein alignments using

MUSCLE (Edgar 2004). We then used this alignment and its nucleotide sequences as input into

PAL2NAL (Suyama et al. 2006) using the -nogap flag to remove gaps to generate a codon

alignment. For each orthogroup in turn, we ran the PAML (Yang 2007) codeml package run

using the branch-site model (Zhang et al. 2005) to evaluate the fit to the sequence data of a

model in which regions of the coding sequence are under positive selection for amino acid

variation along a focal (foreground) branch and not on any other branch from the tree (the

background branches). We used as input to PAML the codon alignment for the orthogroup and

the topology of the phylogenetic tree relating the species (as in Figure 1A), omitting *K.*

siamensis. The calculation proceeded in two steps. First, we fit a null model in which all

branches of the tree had the same protein evolutionary rate (PAML codeml run with options

verbose = 1, seqtype = 1, clock = 0, model = 2, NSsites = 2, fix_omega = 1, omega = 1),

yielding a protein evolutionary rate and log-likelihood of the data under the model. Next, we re-

fit using an alternative model in which the branch leading to *K. marxianus* was the foreground

(PAML codeml run with options verbose = 1, seqtype = 1, clock = 0, model = 2, NSsites = 2,

fix_omega = 0). Outputs were the codon sites assigned to the class with an excess of amino

acid changes in *K. marxianus* relative to silent changes, and their posterior probabilities under

Bayes Empirical Bayes inference (Yang et al. 2005); the codon sites assigned to classes with

relaxed and purifying selection, respectively, along the background lineages, and their posterior

probabilities; and the log-likelihood of the data under the model. The *p*-value assessing the

improvement in fit to the data of the alternative model relative to the null was calculated from a

likelihood ratio test (a χ^2 test on twice the difference of likelihoods with one degree of freedom).

p-values were corrected for multiple testing by the Benjamini/Hochberg method using the

multipletests function from statsmodels (Seabold and Perktold 2010). In Figure 5A we tabulated

all genes with adjusted $p < 0.05$ from this test that had more than 1% of codon sites assigned to

the class with an excess of amino acid changes in *K. marxianus* (proportion in class 2a > 0.01

in codeml). Separately, we repeated the above analyses using the branch leading to *K. lactis* as

the foreground. Conservation of sites called significant by PAML using *K. marxianus* as the

foreground were calculated using Biopython (Cock et al. 2009) to count the conservation of

each site among our sequenced *K. marxianus* strains (Table S1 and see Section 7.3).

Saccharomyces orthologs were taken from (Sorrells et al. 2018).

To complement our PAML analysis, we also ran HyPhy aBSREL (Pond et al. 2005) on the

PAL2NAL alignments across *Kluyveromyces* orthologs as described above. aBSREL uses a

branch-site model similar to PAML to detect positive selection on individual branches. We ran

aBSREL indicating either *K. marxianus* or *K. lactis* as the foreground. We pulled the *p*-value as

calculated by aBSREL for each orthogroup and corrected for multiple testing by the

Benjamini/Hochberg method using the multipletests function from statsmodels (Seabold and

Perktold 2010). *Saccharomyces* orthologs were taken from (Sorrells et al. 2018). We compared

HyPhy aBSREL hits against PAML branch-site hits to confidently list genes acted on positive

selection in *K. marxianus.*

6.3. Resequencing and analysis of K. marxianus *and* K. lactis *population genomes*

For resequencing, we cultured, in 10 mL of liquid YPD, each of five *K. marxianus* strains of non-

domesticated provenance beside Km31, and two non-domesticated *K. lactis* strains beside

yLB72 (Table S1), and we isolated DNA from each with the Quick-DNA™ Fungal/Bacterial

Miniprep Kit (Zymo Research). Genomic DNA sequencing libraries were made and sequenced

on an Illumina NovaSeq 6000 by the UC Berkeley Vincent J. Coates Genomic Sequencing

Laboratory. We used Minimap2 (Li 2018) to map the *K. marxianus* reads to our *K. marxianus*

Km31 reference genome (see Section 5.3). Separately, we mapped the reads from each of 41

K. lactis strains previously sequenced (Friedrich et al. 2023), and those from our two sequenced

K. lactis strains, to our *K. lactis* yLB72 reference genome. For each strain we sorted mappings

using the SAMtools fixmate and markdup functions, and we called single-nucleotide

polymorphisms and generated a pseudogenome as in Section 5.3, except the variant filtering

included only a quality score (QUAL) threshold of above 20. Called variants are provided in

Supplementary Data 2. For each pair of orthologous genes between *K. marxianus* and *K. lactis*

from section 5.3, we aligned the nucleotide sequences of the coding regions from all strains of

the two species using MUSCLE (Edgar 2004). We then used this alignment and its associated

nucleotide sequences as input into PAL2NAL (Suyama et al. 2006) using the -nogap flag to

remove gaps to generate a codon alignment.

For Figure 4D,E and Table S6,7 we carried out per-gene McDonald-Kreitman analyses

(McDonald and Kreitman 1991) on the PAL2NAL alignments using the mktest function from the

CodonAlignment class from Biopython. *p*-values were corrected for multiple testing by the

Benjamini/Hochberg method using the multipletests function from statsmodels (Seabold and

Perktold 2010). For a given gene, this approach tabulates the rates of non-synonymous

polymorphism within species (P_n), synonymous polymorphism (P_s), non-synonymous

divergence between species (D_n), and synonymous divergence (D_s), and the neutrality index NI

= (P_n/P_s)/(D_n/D_s). Because low counts of amino acid polymorphism can drive significance in the

McDonald-Kreitman framework, we developed a filtering scheme in which we tabulated the

average a and standard deviation σ of P_n/P_s across all genes for which we had sequence data.

We only retained for Figure 5D and NI genomic analyses those genes with $P_n/P_s > a - 1.5\sigma$.

For genomic analyses of P_n/P_s and D_n/D_s in the McDonald-Kreitman framework in Table S7, we

used Gene Ontology term assignments and resampling (using 10,000 resamples) as in Section

5.4, except that we only included Gene Ontology terms containing 10 genes or more after

filtering, and for P_n/P_s we tested for enrichment of low values of the metric across a given term.

Genomic analyses on NI proceeded as above, except on the filtered dataset of genes with P_n/P_s

$> a - 1.5\sigma$ as explained above and testing for enrichment of low values of the metric across the

term. p-values were corrected for multiple testing by the Benjamini/Hochberg method using the

multipletests function from statsmodels (Seabold and Perktold 2010).

7. *FAT3* allelic swap mutant generation and cerulenin with oleic acid growth phenotyping

To search for *K. marxianus* phenotypes that *FAT3* could be implicated in, we assayed the

genus in media with cerulenin and oleate according to the Tecan 96-well plate experimental

design described in Section 2, except media contained 500 μM oleate (Sigma) and 0.5% Tween

40 (Sigma) with or without 25 μM cerulenin (from 20 mg/mL stock in ethanol; Cayman

Chemical). We gathered final OD readings as an efficiency read out and tested for significance

with a Mann-Whitney U test from SciPy.

We made $\Delta DNL4$ mutants of *K. marxianus* Km31 and *K.* lactis yLB72 as described in (Rajkumar

and Morrissey 2022). We then made CRISPR/Cas9 plasmids to target each species' *FAT3*

allele in the $\Delta DNL4$ mutants. We chose gRNAs for *K. marxianus* based on the dataset

generated from sgRNAcas9 (Xie et al. 2014) in (ref above), and chose gRNAs for *K. lactis* using

CCTop (Stemmer et al. 2015). Alongside the CRISPR plasmids we made repair fragments by

PCR, with 1kb regions of the species' native gDNA flanking the opposite species' *FAT3* allele to

allow for homologous recombination. We transformed the stitched amplicon and CRISPR

plasmid into *K. marxianus* and *K. lactis* ΔDNL4 mutants by electroporation (Hsu et al. 2021) and

selected transformants by plating onto agar plates with 50 μg/mL of Hygromycin B (Invitrogen

by Thermo Fisher Scientific). Nanopore sequencing of the ~4kb region including the swapped

allele, the flanking homology arms, and the genomic region around it confirmed positive swaps.

We assayed the growth in cerulenin and oleate of *K. marxianus* Km31, *K. lactis* yLB72, and the

FAT3 allelic swaps in either direction to assess the efficiency of *FAT3*. We streaked out *K. lactis*

(Δ*DNL4*), *K. marxianus* (Δ*DNL4*), two replicate clones of *K. lactis* (Δ*DNL4*; *ΔFAT3*::*K. marxianus*

FAT3), and two replicate clones of *K. marxianus* (Δ*DNL4*; *ΔFAT3*::*K. lactis FAT3*) from -80°C

frozen stocks onto YPD plates and incubated them at 28°C for 2 days to allow for colony

formation. We inoculated one colony per strain into 3 ml of YPD and incubated at 28°C

overnight. We then back-diluted the cultures into 10 ml of YPD to achieve 0.05 OD_{600}/ml. We let

the cultures grow at 28°C with shaking for 6-7 hours to reach the early log-phase (0.2-0.4

OD_{600}). We back-diluted the early log-phase cultures into 3 ml of oleate media (YPD with 0.5%

Tween-40, 0.7% KH_2PO_4, 25 μM cerulenin, and 500 μM oleate) or control media (YPD with

0.5% Tween-40 and 0.7% KH_2PO_4). We incubated the cultures at 28°C with shaking for 24

hours and recorded the OD600 as the final readout for cell density. We ran three technical

replicates per assay with at least 4 independent assays, from streaking to measurements of

OD_{600}.

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Data Availability

Raw RNA-seq reads are available on GEO under series record GSE302710. Genome sequencing data is available on SRA with accession PRJNA1291269.

Figure captions

Figure 1. *K. marxianus* shows a unique heat and chemical stress resistance phenotype that only manifests during its growing stage. A, Each panel reports the results of a growth profiling experiment across the genus in the indicated condition. In a given panel, each trace reports a growth timecourse for the indicated species, with the solid line displaying the mean across technical replicates and the faint outline showing the standard error. OD, optical density. **B**, Each row of serial dilutions reports viability after heat shock of a sample of the indicated species in the indicated liquid growth phase. Schematics show experimental design of heat-shocking cells either at stationary or exponential phase. See Figure S3B for unshocked controls.

Figure 2. Overall regulatory volatility by *K. lactis* relative to *K. marxianus* and distinct regulatory patterns that separate the species. A, Shown are results of principal component (PC) analysis of *K. lactis* (orange) and *K. marxianus* (blue) transcriptomes across treatments. Each point reports the values of the top two PCs for one replicate transcriptome of the indicated species subjected to the indicated stress treatment or a 28°C unstressed control. In a given axis label, the value in parentheses reports the proportion of variance across the set of transcriptomes explained by the indicated PC. **B,C,** Each panel reports the effect of stress on expression of genes of the indicated Gene Ontology term in *K. marxianus* and *K. lactis*. In a given panel each cell reports, for the indicated gene, normalized read counts in the indicated stress treatment and an unstressed control, standardized by row using z-scores.

Figure 3. Gene family expansions in *K. marxianus*. A, The color of each cell reports the

change in copy number, in the indicated genome of a *Kluyveromyces* or related species relative

to its parent node in the phylogeny, of a gene family (orthogroup, OG) with significant expansion

or contraction in the *K. marxianus* genome as inferred with CAFE 5. Transposon and reverse

transcriptase families with significant change values are not listed, see Table S4 for results for

all analyzed orthogroups. **B,** Each panel reports the positions of genes in the *K. marxianus*

genome in one indicated gene family from **A** with annotations as major facilitator superfamily

(MFS) transporters. In a given panel, each row represents a chromosome in *K. marxianus*, and

each arrow reports a gene of the respective family and its transcriptional direction (not to scale).

Figure 4. Phylogenetic analysis reveals accelerated amino acid evolution in *K.*

***marxianus*. A,** Each bar shows the number of genes with significant evidence for positive

selection on the indicated lineage (adjusted $p > 0.05$) in a phylogenetic PAML branch-site test

and HyPhy aBSREL test. **B,** Venn diagram of genes called significant for positive selection in *K.*

marxianus in PAML branch-site and HyPhy aBSREL tests. **C,** Amino acid alignment of an

example region of a gene, KLLA0B02607g (*S. cerevisiae* ortholog FAT3/*YKL187C*), with

evidence for positive selection from the PAML test in **A** and from the McDonald-Kreitman test of

D. Highlighted columns show inferred targets of positive selection from the PAML test in **B**.

Highlighting indicates the amino acid's BLOSUM 62 matrix score with respect to the consensus

amino acid. **D,** Each row reports a gene with evidence for adaptive protein variation between *K.*

marxianus and *K. lactis* according to the McDonald-Kreitman test (adjusted $p < 0.05$). NI,

neutrality index. Genes highlighted in green also showed significant evidence for positive

selection on the branch leading to *K. marxianus* in phylogenetic tests (PAML branch-site

adjusted $p < 0.05$ and HyPhy aBSREL adjusted $p < 0.05$; Table S5). Not shown here are genes

with p-value < 0.05 as a product of exceptionally high or low amino acid polymorphism; see

Methods and Table S5. **E,** Each bar shows the cell density (as OD_{600}/mL after 24 hours of *K.*

marxianus and *K. lactis* and their respective FAT3 allele swaps in media with cerulenin and

oleate, where cerulenin blocks lipid uptake and oleate is the only available lipid for utilization.

The starred comparison between *K. marxianus* and its klFAT3 mutant indicate a statistically

significant difference ($p = 0.0223$). **F**, Each row reports a gene ontology term with significant

enrichment for low NI (adjusted $p < 0.05$) in the McDonald-Kreitman test (Table S5).

Figure 1

Figure 2

A

B — Lipid binding - GO:0008289

- MDM34/KLLA0A01573g
- MDM12/KLLA0C06028g
- OSH7/KLLA0A02827g
- YHR073W/KLLA0C16797g
- MMM1/KLLA0F15796g
- HES1/KLLA0D07480g
- TCB2/KLLA0C13860g
- TCB3/KLLA0B04708g
- OSH2/KLLA0C04147g
- NVJ2/KLLA0C15763g
- COQ2/KLLA0D12320g

28°C 39°C Caffeine Ethanol MMS | 28°C 39°C Caffeine Ethanol MMS

K. lactis | *K. marxianus*

C — Nucleolus - GO:0005730

- RPB9/KLLA0D03234g
- RCL1/KLLA0C05984g
- CGR1/KLLA0E10781g
- RPC11/KLLA0F18568g
- POL5/KLLA0D00792g
- GAR1/KLLA0F21604g
- RYV7/KLLA0D05445g
- SLX9/KLLA0C15565g
- UTP15/KLLA0F13772g
- MAK16/KLLA0A04037g
- NIP7/KLLA0B02266g
- NOP7/KLLA0D15268g
- NSA2/KLLA0E13619g
- NHP2/KLLA0C15345g
- MRT4/KLLA0B13563g
- NSA1/KLLA0F10593g
- SNU13/KLLA0E22529g
- NOG2/KLLA0C18843g
- NOG1KLLA0E24135g

28°C 39°C Caffeine Ethanol MMS | 28°C 39°C Caffeine Ethanol MMS

K. lactis | *K. marxianus*

-1.0 -0.5 0.0 0.5 1.0
Normalized expression z-score

Figure 3

A

Gene Family Expansion and Contractions

B

Figure 4

A

PAML branch-site

HyPhy aBSREL

B

491 | 51 | 29

PAML | HyPhy

C

K. lactis

K. marxianus

K. dobzhanskii
K. wickerhamii
K. aestuarii
K. nonfermentans

Consensus: E V I T E D D I N E I M P D I L S Y L N I A E R F R L G I F S Y C R V S S D G D V L S C S N P H A V Q G L D M K E I L Y T E L

D

K. lactis, K. marxianus genes	NI	Saccharomyces gene	Standard Name	Function
KLLA0E09329g, KM020H00950	0.19	YOR020W-A	MCO10	Subunit I of the mitochondrial F1F0 ATP synthase
KLLA0E07569g, KM020D04120	0.26	YKL060C	FBA1	Fructose 1,6-bisphosphate aldolase
KLLA0D10780g, KM020E01340	0.32	YJR118C	ILM1	Unknown function, possible mitochondrial involvement
KLLA0C12133g, KM020E02920	0.39	YNL284C	MRPL10	Mitochondrial ribosomal protein
KLLA0A10175g, KM020A03410	0.47	YMR313C	TGL3	Triacylglycerol lipase and LPE acyltransferase
KLLA0F19162g, KM020D01640	0.49	YDR111C	ALT2	Catalytically inactive alanine transaminase
KLLA0B04994g, KM020F01720	0.50	YLR443W	ECM7	Putative integral membrane protein, calcium uptake
KLLA0F00528g, KM020F00240	0.51	YAL061W	BDH2	Putative medium-chain alcohol dehydrogenase
KLLA0B02607g, KM020D05580	0.59	YKL187C	FAT3	Fatty acid uptake
KLLA0D16236g, KM020F04880	0.63	YGR130C	N/A	Component of the eisosome
KLLA0F26048g, KM020E04040	0.68	YMR066W	SOV1	Mitochondrial protein of unknown function

E

F

GO Term	GO Term Function	NI mean
GO:0006096	glycolytic process	0.7180
GO:0015986	proton motive force-driven ATP synthesis	0.7693
GO:0055085	transmembrane transport	1.0418
GO:0005975	carbohydrate metabolic process	0.9794
GO:0006099	tricarboxylic acid cycle	0.8911

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