**Enabling in-depth characterization of complex multi-knockout traits using engineered population profiling**

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**Abstract**

Many biological traits are controlled by an underlying multi-gene system. Key to the understanding of many such systems is the discovery and characterization of their unexpected multi-knockout phenotypes. Here we develop and demonstrate an ‘engineered population profiling’ strategy to study arbitrarily complex genetic relationships within a targetted gene set. We create an extensive multi-knockout phenotype map amongst 16 yeast ATP Binding Cassette (ABC) transporters through engineering, genotyping, and resistance profiling of ~7,000 yeast strains containing random knockout combinations grown under the effects of 16 drugs. Analysis of this multi-knockout phenotype map led to many new context-dependent transporter-transporter relationships, especially involving *YBT1* and *YCF1*. Amongst the findings, a quadruple knockout conferred unexpected resistance to the *PDR5* substrate fluconazole, leading to development of a new model of complex mutual inhibition amongst the involved transporters. This engineered population profiling strategy allows in-depth genetic characterization of targetted gene sets.

**Introduction**

The function of a gene in the context of a living system is often understood by observing the effects on the organism when it is perturbed or varied. However, dependency and functional redundancy in biological systems results in many traits which cannot be straightforwardly understood as a combination of single-variant effects1–4. In many cases, organization of genes into functionally dependent pathways or complexes results in surprising multi-knockout effects, broadly termed ‘genetic interactions’. Thus, accurate understanding of how a gene contributes to a biological function often requires uncovering and accounting for its phenotypic effects in the context of other genetic variants. Studying such interactions can reveal the organization of functional dependencies in the cell, creating a map of cell function5.

A challenge to systematically studying multi-gene variant or knockout effects are the vast number of potential combinations. While single-knockout effects have been widely profiled in many organisms, a genome-wide profile of genetic interactions in yeast required the development of tools to individually engineer and profile more than 23 million strains containing two-gene knockout combinations5. Large two-gene knockout profiles like these have been used to accurately cluster genes into functional groups5,6, to better predict the genetic basis of drug resistance7, and to inform order-of-action in biological pathways8. Despite the scale of such efforts, approximately 1,000 yeast genes remain with no single-knockout growth phenotypes and few or no two-gene interactions under standard growth conditions5. While it is expected that many of these genes would reveal a phenotype in a genome-scale three-gene knockout screen, such a screen would require the engineering and phenotyping of more strains than is currently feasible.

While multi-knockout phenotypes have been challenging to explore using existing approaches, they are likely to affect many biological traits. A large survey of triple knockout phenotypes in yeast predicts that three-gene interactions would greatly outnumber all discovered two-gene interactions if mapped genome-wide9. Consistent with this, a survey of individual examples shows that they can arise from many different underlying mechanisms, and may thus be prevalent within many biological systems10. Extending beyond three knockouts, individual examples of complex genetic interactions involving 5+, 7, and 20+ simultaneous mutations have been reported in this model organism11–13, but their general prevalence is unknown. A formal approach to capture complex genetic interactions in a collection of published multi-gene perturbation experiments shows that they can have large effects which are comparable to or greater than those seen with single gene knockouts14. Despite their prevalence and potentially large effects, however, general understanding of mechanisms leading to complex genetic interactions and their contribution to genotype-to-phenotype relationships remains far behind the analgous understanding of two-gene knockout effects.

To surmount the combinatorial complexity required to study complex multi-knockout phenotypes, methods are needed to efficiently engineer and genotype the required strains. Many molecular tools used to study two-gene knockouts were developed for the engineering of many strains with a few deletions, and are not easily adaptable for the engineering of many multi-deletion strains due to the limited availability of usable molecular markers15. To make modifications at multiple loci simultaneously, several multiplex automated genome engineering (MAGE) methods have been designed16,17. However, such methods often aim to isolate a handful of engineered strains exhibiting a phenotype of interest, and are not designed to genotype the large number of strains required to create an in-depth genotype to phenotype map. To extend MAGE for these purposes, methods are under development in *E. coli* to allow the genotyping of many engineered strains at multiple loci18,19. In principle, MAGE-like methods can serve as the basis for creating the genetic variation required to understand phenotypes resulting from multiple genetic modifications, and are likely to do so in the near future.

With the aim of profiling arbitrarily complex genetic relationships within a gene family, we had previously developed a method for knocking out multi-gene redundancies, and had deleted 16 ATP Binding Cassette (ABC) transporters in a single yeast strain (ABC-16)15. ABC transporters are part of a large, functionally redundant, and conserved gene family with over 10,000 members across all three domains of life20, and are important for roles such as multidrug resistance, disease progression, and basic cellular functions21,22. Using the ABC-16 strain, we demonstrate an ‘engineered population profiling’ strategy to study arbitrarily complex drug resistance knockout phenotypes within the 65,536 possible knockout combinations in this targetted set of genes. To this end, we first back-crossed the ABC-16 strain to a pool of isogenic wild-type parents, each containing a unique DNA barcode23. We successfully genotyped 6,709 progeny from this cross *en masse*, linked the genotype to a strain-specific barcode, and performed genotype-indexed growth profiling using high-throughput barcode sequencing under 16 drugs23. We use these profiles to uncover numerous surprising and reproducible multi-knockout relationships, leading to a map of many novel drug-dependent transporter-transporter relationships, and many new roles for *YBT1* and *YCF1*. Further exploration of a multi-knockout trait pointed to a new model of complex mutual inhibition amongst ABC transporters, and demonstrates the potential of targetted profiling strategies to map phenotypes controlled by multiple genes and inform understanding of gene function.

**Results**

**Creation and Profiling of an Engineered Population**

In order to engineer a population of strains containing random multiple knockouts within a targetted set of genes, we used our previously-created ABC-16 strain15. ABC-16 was mated to a pool of isogenic wild-type strains containing two unique DNA ‘barcode’ tags (UP and DN) to allow molecular identification of each individual in the population. After sporulation and barcoded haploid selection, automated colony picking was used to isolate ~10,000 MAT**a** and MAT**α** progeny into 384-well plates, creating a collection of strains containing random knockouts. To genotype these progeny *en masse* and link this information to their DNA barcode, we adapted our previously-developed row-column-place PCR (RCP-PCR) protocol24 to amplify and sequence the strain-specific barcodes as well as barcodes identifying the deletion of specific genes. Here, the RCP-PCR products were tagged with DNA sequences indicating the plate as well as the row and column of origin, allowing high-throughput sequencing to identify which strain- and deletion-specific barcodes came from the same well in the collection (Methods; Fig. 1). To calibrate the genotyping results obtained by high-throughput sequencing analysis, multiple replicates of 40 individually genotyped ‘gold standard’ strains, as well as two additional control strains were added to the collection at known positions (Methods; Data S2). Using these strains, we estimate a genotyping accuracy of 95% or higher for 12 of 16 genes, and an overall accuracy of 93.2% (Fig. S1A, Methods). An independent method based on the distribution of knockouts in the genotyping data estimated a similarly high overall accuracy of 93.8% (Fig. S1C, Methods). Based on the pool genotyping data, all genes were either unlinked or weakly linked except for *BPT1* and *YBT1* (Fig. S1B; r = 0.49). Surprisingly, three pairs of genes – *YOR1-YCF1*, *YOR1-BPT1*, and *SNQ2-PDR5* – had weak (-0.04 ≥ r ≥ -0.08) but significant apparent negative linkage (Fig. S1B). These small effects may have arisen during the sporulation, haploid selection, or automated colony picking steps. Overall, usable genotyping data linked to at least one unique DNA barcode was obtained for 6,709 progeny with 5,095 unique genotypes.

After validating the genotyping results and determining a unique barcode for many strains, we profiled resistance to a collection of drugs. The arrayed collection was transferred into two liquid pools separated by mating type (MAT**a** and MAT**α**), which were treated as independent populations in subsequent analyses. These pools were grown in the presence of 16 different anticancer and antifungal drugs (Data S3), as well as a solvent control. Using high-throughput strain barcode sequencing23, strain frequency was estimated at five time points (0, 5, 10, 15, 20 generations of overall pool growth, Fig. 1). Sequencing data from all time points were used to determine an overall growth metric for each strain, and resistance was determined by comparing growth in each drug to the solvent control (Methods, Fig. 1). After excluding individuals with missing barcodes, resistance scores were determined for 3,221 MAT**a** and 3,592 MAT**α** strains (Data S5). To evaluate pool complexity, we measured correlation between the resistance scores generated by the UP and DN barcode tags. Resistance scores for 8 drugs were highly correlated (r > 0.9 for both MAT**a** and MAT**α** populations), and moderately correlated (minimum r > 0.7) for 4 other drugs (Fig. S2 A,B). The remaining 4 drugs had low strain to strain variability, suggesting that the 16 ABC transporters tested did not play a major role in mediating resistance to these compounds (Fig. S2C).

**A Landscape of Complex Multi-Knockout Effects**

In order to explore multi-knockout effects in depth, we aimed to first identify genes relevant for resistance to each drug. For this purpose, we used a linear model to determine marginal associations of each knockout to drug resistance. This approach tests for significant knockout effects when aggregated over all genetic backgrounds in the population. While prior reports had been largely focused on the effects of *snq2∆*, *pdr5∆*,and *yor1∆*, we found many unreported associations with *ycf1∆*, *bpt1∆*, and *ybt1∆* to be common amongst the drugs tested (Fig. S3, Data S6). The latter three knockouts had comparably small marginal effects, which may result either from their potentially minor roles towards resistance to the tested drugs, or their greater dependence on specific knockout backgrounds. Of the significant marginal associations found, 62% were reproducible between the MAT**a** and MAT**α** pools (Fig. S3). From these reproducible associations, we verified 16 of 21 previously-known single-knockout resistance phenotypes (Fig. S3; Data S7). Models made from pooled resistance data of one mating type predicted knockout phenotypes of the opposite mating type equally well (Fig. S4), indicating generalizability in the population resistance patterns.

We used the population resistance data to explore all combinations of multiple knockout effects amongst *snq2∆*, *pdr5∆*, *yor1∆*, *ycf1∆*, *bpt1∆*, and *ybt1∆* in the tested compounds. Strains in the pool were grouped based on their genotype at these transporters (allowing variation at the other 10 transporters within each group). These groups represent a reduced resistance profile for each population, which can be used to cluster drugs by profile similarity (Fig. S5). Expansion of this grouped resistance profile into a ‘complex fitness landscape’ allows visualization of transporter knockout effects in the context of any other knockout combination. This complex fitness landscape revealed many surprising and reproducible genetic relationships under different drugs (Fig. 2A, S6). In the most straightforward cases, sensitive multi-knockout groups were found where removal of a smaller number of the underlying genes had much less apparent effects. These patterns are illustrated, for example, by the *snq2∆pdr5∆* group under camptothecin (Fig. S6), and by the *snq2∆pdr5∆ybt1∆* or *snq2∆pdr5∆yor1∆* groups under mitoxantrone (Fig. 2A). Broadly, such complex sensitivity patterns suggest that multiple transporters are able to efflux a given drug redundantly.

In several cases, the fitness landscapes involved complex multi-knockout patterns mediating both drug resistance and sensitivity. Under benomyl, for example, the effects of *yor1∆* were highly context dependent – *yor1∆* was not found to have a significant effect relative to the six-gene wildtype group, to increase fitness relative to *pdr5∆* as *yor1∆pdr5∆*, and to decrease fitness relative to *snq2∆* as *yor1∆snq2∆* (Fig. 2A). The *yor1∆pdr5∆* phenotype may have been expected given *SNQ2*-mediated benomyl resistance and an earlier report of a (non-additive) ‘compensatory activation’ of Snq2 given disruption of *PDR5* and *YOR1*25. However, the *yor1∆snq2∆* phenotype is novel and suggests that Yor1 may also serve a secondary role in benomyl resistance, for example by providing some efflux in the absence of Snq2. Multiple knockout combinations also conferred surprising drug resistance. Under fluconazole and ketoconazole, a quadruple deletion – *snq2∆ybt1∆ycf1∆yor1∆* – led to resistance, whereas *pdr5∆snq2∆ybt1∆ycf1∆yor1∆* was comparably as sensitive as the *pdr5∆* group (Fig. 2A, S6)*.* Furthermore, combinations of one or two knockouts within these four genes resulted in minor effects (Fig. 2A, S6). These effects extend the previously-reported compensatory activation25, but require multiple knockouts and the involvement of *YCF1* and *YBT1*.

While a traditional ‘linear’ fitness landscape allows visualization of all context-dependent knockout effects, these data may also be used to explore all possible paths towards a complete knockout state. To represent these paths, we developed a ‘radial’ fitness landscape to draw them explicitly, and in a top-down format which allows for a broad overview (Fig. 2B–C, S7). Relevant knockout combinations and the complexity of knockouts required to confer large differences in resistance are readily visualized (Fig. 2C). Path structures are highly dependendent on the compound used, consistent across independent populations, and in many compounds multiple paths led to ‘peaks’ conferring more resistance than the wild type state (Fig. 2C).

Because each group contains a heterogeneous population of cells with additional background knockouts, we further explored their underlying distribution in the context of fluconazole resistance (Fig. 2D). This revealed that variance within the *pdr5∆* groups is much less than groups containing *PDR5*. The lack of variability in the *pdr5∆* groups may be explained by the unconditionally high fluconazole sensitivity of these strains, whereas the variability in the *PDR5* groups may reflect still-unidentified and more complex ABC transporter knockout effects in these genetic backgrounds.

**Formal Capture of Complex Genetic Interactions**

After observing many apparently-surprising multi-knockout drug resistance phenotypes, we aimed to formally capture the complex genetic interactions present within the engineered population. We used a linear model to extend the multiplicative model of combined genetic effects26 to incorporate potential interactions (noted by ε) of arbitrary complexity (see Methods). We treated the search for complex genetic interactions as a feature selection problem, and tested for the presence of up to to 4-gene interactions within a total space of 2,516 coefficients (See Methods; Fig. 3A). We found 23 2-way, 12 3-way, and 8 4-way interactions which were consistent between the MAT**a** and MAT**α** pools at a stringent Bonferroni corrected p-value cutoff of 0.05 (Data S6).

This approach formalized many of the apparently-surprising genetic relationships found in the fitness landscapes. For example, *yor1∆* was found to have no main effect under benomyl, to have a positive genetic interaction with *pdr5∆*, and to have a negative genetic interaction with *snq2∆* (Fig. 3A, Data S6). In camptothecin, *pdr5∆* and *snq2∆* each had a minor main effect, as well as a strong negative interaction between them (Fig. 3A, Data S6). Similarly, the surprising phenotype in mitoxantrone was modelled as a combination of a small marginal effect of *snq2∆*, a negative interaction , and further triple negative interactions upon *YBT1* and *YOR1* deletions as and (Fig. 3A, Data S6). This pattern of genetic interactions suggests not only that these three genes efflux mitoxantrone in parallel, but also a differential efflux capacity between them (i.e. Snq2 has the largest efflux potential because it is the only one which shows a single-knockout defect). A similar ‘parallel transport’ phenotype was observed for *pdr5∆ snq2∆* and *yor1∆* in cisplatin (Fig. 3A, Data S6). Under fluconazole, the resistance phenotype was modelled (in addition to one- and two- gene effects involving *pdr5∆*, *yor1∆*, and *ybt1∆*) as the combination of three positive triple interactions (, , ). The dependence of these effects on *PDR5* were then further modelled as three additional negative four-way interactions(, , ).

**Integrating Multi-Knockout Phenotypes into Drug-Dependent Transporter-Transporter Relationships**

Given the grouped fitness landscapes and formally-determined genetic interactions, we manually interpreted a set of transporter-transporter relationships. These relationships were highly drug-dependent, and were derived from either two, three, or four knockout phenotypes (Fig. 3B, Data S8). We modelled all relationships as involving either parallel clearance of a drug by two or more transporters, and/or the antagonism of an ABC transporter by the presence of another (Fig. 3B). These models suggest an extensive role for *YBT1* and *YCF1* in many drugs – *YBT1* is hypothesized to work in parallel with *SNQ2*, *PDR5*, or *YOR1* in the context of mitoxantrone, itraconazole, and methotrexate resistance, and to antagonize *PDR5* in the context of fluconazole resistance (Fig. 3B). *YCF1* is modelled to antagonize *SNQ2* in bisantrene resistance, to antagonize *PDR5* in fluconazole and ketoconazole, and to work in parallel with *SNQ2* in the context of benomyl resistance (Fig. 3B). Because these genes had absent or subtle single-knockout effects in many drugs, these relationships are likely to have been missed in traditional knockout screens.

**Single-Strain Validation of Population-Based Genetic Interactions**

In order to validate the complex genetic interactions present in the population, we used targetted crosses to generate individual strains containing all knockout combinations of *pdr5∆, snq2∆, yor1∆, ybt1∆,* and *ycf1∆* (Methods). With this population, we tested the multi-knockout resistance patterns for XX drugs under non-competitive liquid growth environments. It was found that XX. Fluconazole resistance of these individual strains correlated well with the pooled resistance (r=XX, Fig XX). As predicted by the pool data, the *snq2∆yor1∆ybt1∆ycf1∆* strain was the fastest growing, and only minor resistance effects were seen for strains with one and two knockout combinations amongst these four genes.

A targetted collection of individual strains readily allows testing of the relationships of multiple knockouts to a drug response at multiple concentrations. We used this collection to better evaluate the dependence of the increased resistance observed in the *snq2∆yor1∆ybt1∆ycf1∆* strain on the presence of *PDR5.* We reasoned that at concentrations where the *pdr5∆* strain exhibits some growth, partial rescue effects which are missed at higher concentrations will be apparent. At such concentrations (1.3μm; XX% inhibition of *pdr5∆*), it was found that all *pdr5∆snq2∆* strains, including *pdr5∆snq2∆yor1∆ybt1∆ycf1∆* grew worse than *pdr5∆* strains (Fig XX), while there was no partial rescue evident in the *pdr5∆yor1∆ybt1∆ycf1∆* strain. This suggests that *snq2∆* can simultaneously act as a minor efflux pump for fluconazole in addition to its inhibitory effect, allowing its knockout to result in different drug resistance phenotype at different concentrations. Ultimately, these data support a model where multiple gene deletions modulate the level or activity of Pdr5.

**Pdr5 is inhibited by XX through XX**

Given the genetic evidence of repression of Pdr5 by the presence of *SNQ2*, *YOR1*, *YBT1*, and *YCF1*, we sought to understand the underlying mechanisms. Inhibition of Pdr5p by *SNQ2* and *YOR1* has been previously reported, and thought to be mediated by transcriptional activation by Pdr125, although the mechanism underlying this compensatory activation is unknown. To investigate whether *PDR5* mRNA abundance was elevated in the *snq2∆yor1∆ybt1∆ycf1∆* compared to the wild type and *snq2∆yor1∆*, we performed qRT-PCR in both the solvent control and fluconazole. In both the solvent control and fluconazole, *PDR5* transcript abundance was elevated in the *snq2∆yor1∆ybt1∆ycf1∆* strain relative to the wild type strain (p = 0.039 in DMSO; p = 1.6 x 10-3 in fluconazole; Fig XX). However, we did not find evidence of increased *PDR5* transcript levels in the *snq2∆yor1∆* strain (p = 0.366 in DMSO; p = 0.15 in fluconazole; Fig. XX). This is consistent with the lack of improved fluconazole resistance of this strain (p = XX, Fig. XX) and suggests strain-specific differences in the induction phenomenon. Thus, while we observed transcriptional activation of *PDR5*, here we required additional knockouts in *ybt1∆* and *ycf1∆*.

As an alternative mechanism of *PDR5* repression by Snq2 and Yor1, we investigated the possibility of a protein-protein interaction based mechanism. A previous study investigating an analogous compensatory activation of Snq2 by deletion of *PDR5* and *YOR1* found unchanged protein abundance and localization upon knockout of these two genes, and suggested that physical interaction between these two proteins may lead to their mutual repression27. We also noted that homodimers of Pdr5p, Snq2p, and Yor1p have been detected using the mDHFR protein complementation assay (PCA)28,29, and that the Pdr5p homodimer has also been detected using the membrane yeast-two-hybrid (MYTH)27 assay. Furthermore, an interaction has been reported between Pdr5p and Snq2p with both assays27,28. If these proteins require homodimerization to efflux their given drugs, or the heterodimer forms are otherwise unable to perform this function, then it would be predicted that deletion of any of these genes may shift ABC transporter complex levels towards a greater abundance of their active form. However, this model also predicts the presence of a previously-unreported Pdr5p-Yor1p interaction. We re-tested a potential Pdr5p-Yor1p interaction, and found it using MYTH but not PCA (Fig. ?? XX), lending consistency to the PPI-based repression model.

Given both evidence for transcriptional feedback and consistency with the PPI-based repression model, we tested whether the transcriptional induction is sufficient for the observed increase in resistance. To do this, we removed all endogenous control of *PDR5* by expressing it in a plasmid under the control of a constitutive promoter in the *pdr5∆*, *pdr5∆snq2∆yor1∆*, and *pdr5∆snq2∆yor1∆ybt1∆ycf1∆* strains. However, this still allows for mechanisms such as PPI-based repression to take effect. We found XX.

that the repression appears to be bi-directional for Pdr5p and Snq2p, both in our data (XX Fig ?? XX) and from previous reports25, we hypothesize that the homodimeric form of Pdr5p may be responsible for the efflux of its respective drugs, and that the formation of Pdr5p::Snq2p and Pdr5p::Yor1p heterodimers may deplete the concentration of Pdr5p::Pdr5p homodimers available for efflux.

**Discussion**

Here we engineered and profiled a large population of strains containing combinatorial gene deletions, and discovered many unexpected multi-gene knockout effects leading to numerous new roles for the 16 ABC transporters studied. Many knockout phenotypes were highly dependent on the combination of drug stress and knockout background, and we envision that studies of other gene families or pathways would reveal similarly-complex patterns. While principles guiding mechanistic understanding of complex genetic interactions are currently limited, we found that with some prior knowledge of gene function, complex multi-knockout effects can be functionally interpreted and used to construct clear follow-up experiments and models. Here we hypothesized all complex genetic patterns to result from a combination of parallel clearance and antagonism between transporters. Amongst these relationships, novel roles were found for *YBT1* and *YCF1* in mediating both resistance and sensitivity to the tested compounds, which may have been missed due to their subtle or absent single-knockout effects in a wild-type background. For example, the complex drug resistance phenomenon observed in fluconazole extends previous reports of compensatory activation between ABC transporters25,27 to include *YBT1* and *YCF1*. We note that the human ABC transporter ABCC3 has also been shown to exhibit compensatory activation upon knockout or disruption of ABCC2, both in rat knockout models30, and in the context of Dubin-Johnson syndrome31, motivating similar genetic studies of this gene family in other model organisms. Several drugs also exhibited multi-knockout sensitivity patterns, suggesting overlapping substrate specificity which could affect studies of ABC-transporter mediated drug clearance. Overall, we demonstrate that even within a highly-characterized gene family, engineered population profiling has the potential to reveal many new functions.

Here, a previously-engineered ABC-16 strain allowed the use of a cross-based strategy to efficiently introduce mutations into a population of cells. In previous yeast studies, profiles of individuals from controlled crosses have been used to study complex traits such as gene expression32 and resistance to small molecules33. In more complex model organisms such as mice, initiatives like the collaborative cross project have made use of controlled crosses between inbred strains to create numerous defined heterozygotes that can be used to study both the variability and genetics of mouse traits34. The engineered population design extends these cross-based methods by limiting the genetic variation to include only targetted modifications within a defined set of genes, creating a clear link from association to causality. Efforts to introduce targetted gene knockouts35 or loss-of-function mutations36 into model organisms such as *C. elegans* may enable the use of this strategy with future engineered multi-knockout parental strains. The initial parental strains for such crosses may be generated by a series of targetted matings, and now more straightforwardly with the use of modern genome engineering tools such as CRISPR. A cross-based strategy allows flexibility in the distribution of knockouts between the two parents, and may be useful in cases where introducing all knockouts into a single parental strain would cause considerable defects or lethality. In such cases, the use of conditional alleles or similar tools to suppress complex synthetic lethality when creating the population may also be useful37.

As an extension to cross-based methods, development of new tools would allow introduction of multi-allele diversity directly into a population. Direct population engineering would also allow for the study of complex multi-knockout phenotypes in model systems where mating is not possible, such as human cell lines. For example, this extension would further enable similar studies of human ABC transporter function. We note that methods which aim to achieve direct population-level engineering are under development in *E. coli*19. However, such methods must precisely introduce engineered variation to many strains at multiple loci at intermediate frequency, and this is a major are of future development.

A greater ability to genotype many strains would constitute a major improvement to future engineered population profiling methods. The *en masse* RCP-PCR based method used here allowed for genotyping which was orders of magnitude faster than traditional approaches, but first required the isolation and storage of strains into a defined collection. Linking genotype to a DNA barcode in a direct pooled format without isolating and performing a separate PCR reaction on each strain would therefore allow the profiling of substantially more strains than is currently possible. We note that despite the complex multi-knockout phenotypes discovered, the majority of knockout combinations amongst the 16 ABC transporters (~92%) remain to be characterized, and even a study within this limited set of genes would benefit from the ability to perform more efficient genotyping. Furthermore, such methods would enable the discovery of even more combinatorially complex interactions involving multiple alleles at multiple genes, enabling very precise and detailed genetic maps which reflect the variation present in real populations, while allowing for complete allelic control4.

In addition to the context-dependent growth measured in this study, many traits can be measured and linked to a specific genotype *en masse*. For example, to understand drug efflux, cells may be exposed to a fluorescence-conjugated drug, and fluorescence-activated cell sorting at different time points coupled with barcode sequencing may recreate efflux dynamics for many strains. In a similar fashion, barcode sequencing coupled with cell sorting may be used to reconstruct many phenotypes, for example the effects of knockouts on the activation of signalling pathways, phosphorylation state, epigenetic modifications, or protein abundance38. Furthermore, methods are being developed to genotype large populations of cells after imaging, which would allow relating many multi-knockout genotypes to the complex phenotypes obtained using high content screens39. With the appropriate design, multiple knockouts obtained by population engineering can be related to a wide variety of phenotypes, both simple and complex.

We envision the use of this method as part of a broader approach to understand complex multi-knockout traits, allowing for in-depth genetic characterization of biological systems in multiple organisms. We show that even within a relatively small and well-characterized gene family, many gene functions and gene-gene relationships remained to be discovered. As techniques for the introduction and characterization of large scale genetic variation improve in scale, allelic variety, and complexity of phenotypic characterization, we expect similar methods to be readily applied towards a greater variety of gene families. Given current estimates of the prevalence of complex genetic interactions, we expect they will be better characterized in the future and readily related to biological function. Ultimately, this will allow a much more in-depth understanding many gene functions and gene-gene relationships in the context of a living system.

**Materials and Methods**

**Yeast Strains**

RY0622/GM512 (Green Monster MAT**a**):

*MAT***a** *adp1Δ snq2Δ ycf1Δ pdr15Δ yor1Δ vmr1Δ pdr11Δ nft1Δ bpt1Δ ybt1Δ pdr18Δ yol075cΔ aus1Δ pdr5Δ pdr10Δ pdr12Δ can1Δ::GMToolkit*-**a** (*CMVpr-rtTA KANMX4 STE2pr-Sp-his5*) *his3Δ1 leu2Δ0 ura3Δ0 met15Δ0*

RY0146 (Toolkit-a strain):

*MAT****a*** *lyp1Δ his3Δ1 leu2Δ0 ura3Δ0 met15Δ0 can1Δ::GMToolkit-a (CMVpr-rtTA KanMX4 STE2pr-Sp-his5)*

RY0148 (Barcoder Strain MATα):

*MATα lyp1Δ his3Δ1 leu2Δ0 ura3Δ0 met15Δ0 can1Δ::GMToolkit-α (CMVpr-rtTA NatMX4 STE3pr-LEU2) ho*∆*::Barcoder locus* (UP-tag HpHMX4 DN-tag )

**Media**

**SC (SC-His, SC-Leu, SC-Ura)**

**YPD (+HygroB, +Clonnat, +G418)**

**Creating the Barcoder Plasmid**

A ‘barcoder locus’ flanked by LoxP and Lox2272 sides was added to a pSH47 plasmid backbone expressing GAL1pr-CRE using in-yeast assembly40. This barcoder locus consists of a random 25bp DNA sequence (‘UP tag’) in between two common primer regions (US1 and US2), followed by a HphMX4 cassette, and another random 25bp DNA sequence (‘DN tag’) in between two common primer regions (DS1 and DS2). This barcoder locus was generated using fusion PCR of two synthesized DNA oligomers.

**Generating a Barcoder Strain**

A linear URA3 cassette flanked by LoxP and Lox2272 sites was integrated into the HO gene of the RY0148 strain through transformation to serve as the locus for barcode integration. This strain was further transformed with the barcoder plasmid, and transformants were selected using HygroB containing media. These transformants were then subjected to a 4 day galactose induction to allow for Cre expression. All strains which were unsuccessful in Cre-mediated plasmid recombination were counter-selected by growth in the presence of 5-FOA. Strains surviving the counterselection were then grown in YPD in the presence of HygroB in order to select for successful integration of the plasmid barcode locus. Ten colonies were tested for barcode integration using two sets of primers to verify the strain barcode-specific UP and DN tag - US2 and a sequence complementary to 5’ of the HO gene (US2+5’HO); DS1 and a sequence complementary to the 3’ of the HO gene (DS1+3’HO). PCR products were analyzed using gel electrophoresis.

**Generating Barcoded Random Knockout Progeny**

Mating, sporulation, and haploid selection was performed between the RY0622 ‘Green Monster’ strain (MAT**a**) and the RY0148 barcoder strain (MAT**α**) as previously described15. Using colony plating, sporulation efficiency was estimated at 24% - 1080 colonies grew in SC, 140 colonies grew in SC-His (MAT**a** haploid selection), and 120 colonies grew in SC-Leu (MAT**α** haploid selection). Samples from the haploid pools were plated as a form of quality control. From the SC-His pool, 440 colonies grew in SC-His, 0 grew in SC-Leu, 468 grew in YPD+G418, 13 (~2%) grew in YPD+Nat; from the SC-Leu pool, 0 colonies grew in SC-His, 1600 grew in SC-Leu, 50 (~3%) grew in YPD+G418, 1650 grew in YPD+Nat. The two pools were then grown in YPD+HygroB to select for barcoded haploids. The SC-Leu pool was further grown in SC-Ura to select against barcoder strain parents that may have escaped diploid selection. Using a QPix colony picker, 5,078 colonies were picked from the MAT**a** pool and 5,844 colonies were picked from the MAT**α** pool onto 384 well plates.

**Individual Strain Genotyping**

To genotype each strain at the 16 ABC transporter loci, two PCR reactions were performed for each locus - one to determine the presence of a GFP integration cassette, and another to determine the presence of the wild type gene. Genotyping was performed as previously described15. For the first set of reactions, locus–specific PCR primers from the 5′ flanking sequences of each gene were paired with a common primer complementary to the *GFP* cassette (Data S1). For the second set of reactions, the 5’ locus-specific primers were paired with primers which were complementary to an internal sequence of their corresponding gene (One of two such pairs was used per gene, see Data S1). PCR products were analyzed using gel electrophoresis.

**Creating A ‘Gold Standard’ Genotyped Set**

To create a ‘Gold Standard’ genotyped set, 40 progeny strains (19 MAT**a** and 21 MAT**α**) were subject to individual strain genotyping. For these 40 strains, and for an RY0148 isolate, the strain-specific UP and DN tags were PCR amplified using two sets of primers – US2 and a sequence complementary to 5’ of the HO gene (5’HO); DS1 and a sequence complementary to the 3’ of the HO gene (3’HO). The PCR products were subject to Sanger sequencing. These 40 ‘Gold Standard’ genotyped strains, as well RY0148 and RY0622 were arrayed into the strain collection at defined positions to act as genotyping controls (Data S2).

**Pooled Strain Genotyping**

A previously-developed Row-Column-Plate (RCP)-PCR protocol24 was adapted in order to perform *en-masse* genotyping of the random knockout progeny using high throughput sequencing. This protocol uniquely tags PCR products originating from the same well, by the use of a 5’ tag encoding the well row (R) in forward primers, and a 5’ tag encoding the well column (C) in the reverse primers24 (Data S2). For each well in the collection, four PCR reactions were performed with the following primers: R+U1 and C+U2 to amplify DNA barcodes encoding the UP tags for each gene deletion; R+D1 and C+D2 to amplify the deletion-specific DN tags; R+US1 and C+US2 to amplify the strain-specific UP tag; R+DS1 and C+DS2 to amplify the strain-specific DNTAG. PCR reactions were performed using a Hydrocycler. Plate-specific Illumina adapters (plate tags) were added using an additional PCR reaction as previously described24.

**Analysis of Pooled Strain Genotyping Data**

Pooled Strain Genotyping PCR products were sequenced using an Illumina MiSeq, and the reads were demultiplexed into individual samples corresponding to a plate and well of origin using a Perl script.

For each sample, a genotype calling pipeline determined the strain-specific tag sequences and genotype from the reads. The parameters of this pipeline were trained based on knosn reference sstrain. Cross-validated accuracy for each gene is reported in Fig. S1A.

UP or DN tag identity and a corresponding genotype was successfully determined for 7,195 samples. For 7,030 samples, the UP or DN tag was unique, and for 165 samples, both the UP and DN tag sequences were redundant with another sample where the called genotype was isogenic or highly similar (≤2 differences), indicating the presence of a single strain in multiple wells. When processing the sequencing data, a single strain was randomly chosen to represent each unique UP and DN tag sequence.

**Examining Putative Wild-Type Pool Strains**

For 73 unique MAT**a** strains and 131 MAT**α** strains, pooled genotyping had called the strains as wild-type. Many of these strains were isolated and tested for the presence of one or more gene knockout cassettes by growth in SC-Ura. Out of 96 MAT**α** strains, 74 exhibited no detectable growth in SC-Ura, and likely arose from remaining barcoder parents which had escaped a previous SC-Ura selection step. The genotypes for the these 74 strains were kept as is, while the other 23 strains, as well as 46 untested strains were discarded from the analysis. Out of 45 MAT**a** strains, all exhibited growth in SC-Ura. Individual genotyping was performed for these MAT**a** strains, and was successful for 40 of 45 strains. These strains had their stated genotype was corrected (Data S2). The 5 unsucessfully genotyped strains, as well as 28 additional strains were discarded from analysis. When calculating linkage and distribution of gene knockouts, the wild-type MAT**α** strains were excluded from analysis as they were likely parental strains rather than progeny arising from mating.

**Estimating Genotyping Accuracy by Knockout Distribution**

To lend independent support to the genotyping accuracy determined by gold standard strains, an alternate method was used based on the distribution of knockouts in the population. Since *en masse* genotyping associates barcode sequences with ABC transporter knockouts, the absence of a given barcode implies either a wild-type genotype at that locus or a failure in amplification, sequencing, or calling. Conversely, cases where a wild-type is called as a mutant are expected to be comparably negligible. Excess wild-type calls lead to a reduction in the average number of knockouts in the pool, and can be used to estimate genotyping accuracy. The average number of knockouts in the pool was 7.0, lower than the 8 expected with perfect genotyping. This number was most consistent with an asymmetric genotyping accuracy of 93.8%, compared to the 93.2% derived by comparison to gold standards (Fig. S1C, Methods).

**Indiviual Liquid Growth Profiling**

To measure individual strain growth, the OD600 nm of a 0.0625 OD600 nm starting culture was measured in the appropriate medium every 15 mins using a GENios microplate reader (Tecan).

**Drug Testing for Growth Inhibition**

The effects of 16 different drugs on strain growth were tested to find a concentration which inhibits wild type growth by approximately 20% (Data S3). All drugs used were dissolved in 2% DMSO, which was used as a solvent control. Growth was determined by the Average\_G metric41, which represents the average generation time.

**Population Growth Profiling by High-Throughput Sequencing**

Progeny with at least one mapped strain-specific barcode (Data S2) were combined into two separate liquid YPD + glycerol pools separated by mating type, and kept at −80°C. Samples from the original YPD + glycerol pool were thawn and added to the appropriate drug or solvent containing medium at a final concentration of 0.0625 OD600 nm in 10ml. For the solvent control, a 0 generation sample was immediately harvested for sequencing. After growth to approximately 2 OD600 nm, a sample was taken from each drug for sequencing and cells were resuspended in fresh medium to a final concentration of 0.0625 OD600 nm. This process was repeated until 4 generations of samples were collected. Collected samples corresponded approximately to 5, 10, 15, and 20 generations of growth. Harvested samples were subject to genomic DNA extraction using a YeaStar™ Genomic DNA Kit, quantified using a Qubit® 2.0 fluorometer, and diluted to a final concentration of 20ng/μl. Approximately 350ng of isolated DNA was extracted from each sample and added to 20μL of 2x Platinum PCR SuperMix High Fidelity, 1μL of 10μM F primer, and 1uL of 10μM R primer. F and R primer pairs were PXX+US1/ PYY+US2 and PXX+DS1/PYY+DS2 for the strain-specific UP and DN tag, respectively. PXX and PYY correspond to sequences containing plate-specific Illumina sequencing adapters, as well as tags which were used to demultiplex the samples (See Data S1). PCR products amplified using the following PCR program: 98°C for 30sec; 98°C for 10sec, 60°C for 10sec, 72°C for 1min (24 times); 72°C for 5min; 4°C forever.

PCR products were subject to gel electrophoresis, and 210-220bp bands were isolated, subject to gel purification, and eluted in 60μl tris buffer. DNA yield was quantified in duplicate using a KAPA qPCR assay kit, at 1,000-fold, 10,000-fold, and 100,000-fold dilutions to find a concentration within standard curve range. Samples were pooled to yield approximately equal amounts of DNA, and subject to sequencing using Illumina NextSeq 500 Mid Output kit.

**Sequence Data Processing**

Paired-end Illumina sequencing data were first de-multiplexed using a custom Python script which searches for an exact match to the tag regions of the PXX and PYY primers within each pair of reads. For each strain in each de-multiplexed sample (corresponding to a combination of mating type, timepoint, and drug), strain identification is attempted. To perform this identification, a search is performed for all barcodes matching the sample mating type. If an exact match is not found, up to two ungapped mismatches are permitted to assign a putative strain identity, which is then accepted if there are at least 2 additional mismatches separating this identity with the next closest match (e.g. if 2 mismatches are present with the closest match, then the next closest match must have 4 or more mismatches). This process was performed for both the forward and reverse reads (corresponding to the UP and DN tags) for each strain, and potential cases where the putative strain identity differed between tags were discarded.

All samples with less than 200,000 reads were discarded from the analysis. Additionally, if a sample was discarded for one mating type, the corresponding sample for the opposite mating type was also discarded (e.g. if ‘miconazole t=15 MAT**a**’ was discarded due to lack of coverage, ‘miconazole t=15 MAT**α**’ would also be discarded regardless of coverage).

**Defining a Resistance Metric**

From the sequence data processing, a count was assigned for each strain in a pool under drug sequenced at time (. If both an UP and DN tag for a given strain were successfully linked to a genotype, the UP and DN counts in a given sample were averaged to yield . Otherwise the available tag was used as . The counts in each sample were then converted to a frequency by division with the total count for all strains in that sample:

The frequency of each strain was then converted into a ‘virtual area under the growth curve’ () by first multiplying the frequency at each time point by the expected overall pool growth at that time (, since is defined by the number of generations), then taking the integral over all measured timepoints to (the total number of generations measured). Frequencies between measured timepoints were linearly interpolated.

The drug resistance score of a strain is defined as the ratio of its total growth in a drug compared to its growth in the solvent control , per generation:

**Finding Complex Genetic Interactions using a Linear Model**

The multiplicative model of genetic interactions26 was applied to the metric. In this model, the expected resistance of a double knockout strain in a given drug () is the product of the resistances of the corresponding single knockout strains:

To use this model in an additive rather than multiplicative form, the log of the resistance metric was taken , so that:

A two-gene interaction term is then defined as the deviation of the observed double mutant fitness from this expectation, rather than the traditional linear difference from a multiplicative estimate.

When modelling an expected triple knockout fitness, all relevant two-gene interaction terms are added:

Similarly, a three gene interaction term is the deviation from this expectation:

This definition can be analogously extended for interactions of arbitrary complexity, and signficant terms denote interactions between the corresponding knockouts. The genotype of each strain is encoded using a binary variable, so that if and only if all the corresponding genes in the term are knocked out.

For each sample, a linear model was trained relating genotype to log resistance , including all terms up to a chosen level of complexity. Additionally, each trained model contained terms stating the plate of origin for each strain as a way to account for a potential batch effect.

To perform marginal association, we fitted an initial linear model with no terms, and performed stepwise feature elimination (eliminating the gene with the highest value at each step) until all included terms had a significance level of . Linear model term significance was tested using the Type III Sums of Squares ANOVA implementation given in the car package in R.

To train models containing terms of up to -way complexity, additional steps were performed. First, an initial set of a genes was chosen by testing whether a knockout of the 16 ABC transporters resulted in a significant population-level difference in log-resistance, first in the context of the overall population, then in the context of all additional gene knockouts (where is the desired level of gene-gene interaction complexity to be fit in the overall model). Significant differences were evaluated using a t-test, requiring a value of , where is the total number of genetic background contexts tested for that gene. A linear model including genes passing this test and all of their way interactions was then fit.

To speed up feature elimination, many terms were first heuristically eliminated using cross-validated LASSO regression implmented using the cv.glmnet function in R (using the default parameters of alpha = 1, nfolds = 10, type.measure = ‘deviance’). The λ which minimizes the mean cross validated error value was then chosen, and all terms with a nonzero coefficient at that λ value were selected for further elimination. These terms were subjected to stepwise elimination (again eliminating the gene with the highest value at each step), at a significance threshold of where is the number of terms in the initial linear model.

**Targeted Mating and Selection to Obtain 32 Knockouts**

The TWAS21230902 strain (*pdr10∆ pdr18∆ pdr5∆ snq2∆ ybt1∆ ycf1∆ yor1∆;* Data S2) was subject to individual strain genotyping, confirming the genotype generated using the RCP-PCR based method. This strain (MAT**α**) was mated with RY0146 (MAT**a**), and subject to sporulation and MAT**a** haploid selection15. Individuals from this cross were arrayed onto a 384 well plate, and individually genotyped at *PDR10* and *PDR18*. Strains with no deletions at these genes were further genotyped at *PDR5, SNQ2, YBT1, YCF1,* and *YOR1.* After analysis of genotyping results, one strain of each genotype combination was chosen to create the 32-strain collection. These chosen 32 strains were again individually genotyped at these 5 loci for validation.

**Analysis of Liquid Growth Data**

**MYTH and PCA Assays**

The MYTH and PCA assay were performed as previously described27,28.

**Quantitative RT-PCR**

RNA extraction was performed using the QIAGEN RNeasy® kit. 1μg of isolate was treated with DNAse and analyzed usign an Agilent Bioanalyzer to quantify and verify purity. cDNA synthesis was perfomed using a combination of oligo-DT and random hexamer primers. qPCR on these samples was then performed using a SensiFAST™ Real-Time PCR Kit and Ct values were quantified using a CFX machine.

**Availability of Data and Materials**

**Competing Interests**

The authors declare that they have no competing interests.

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**Author Contributions**

N.Y. & F.R. conceived the experiments. N.Y., L.M, M.G., S.Z. & T.F. performed experiments. A.C. and N.Y. analyzed the data. A.C, F.P.R., & N.Y. wrote the paper.

**Additional Data Files**

**Additional Data S1.** List of primers used in this study.

**Additional Data S2.** Genotyping data in the engineered population. Includes a list of control strains used in high-throughput genotyping, initial genotyping results, re-genotyping of putative wild-type strains, and the final set of genotyping data used.

**Additional Data S3.** Drugs used in this study and their concentration in the pooled growth data.

**Additional Data S4.** List of primer pairs used to multiplex pooled growth sequencing data.

**Additional Data S5.** Growth and resistance metrics obtained for all strains in both the MAT**a** and MAT**α** pools.

**Additional Data S6.** Summary of linear modelling results obtained in this study.

**Additional Data S7.** Previously-known drug knockout associationswithin the 16 ABC transporters and 16 drugs studied.

**Additional Data S8.** Functional interpretations of genetic interactions present in the data.

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**Figures**

**Figure 1.** Overview of the engineered population profiling process.

A strain with 16 ABC transporter deletions was crossed with a pool of wild-type cells, each containing a DNA barcode. Genotype is schematized by the grid drawn in each cell (black = knockout, white = wild type). Diploids from this cross were subject to sporulation and barcoded haploids were then selected. Single colonies were picked and arrayed onto a series of 384-well plates. *En masse* genotyping was performed on this collection using an adapted RCP-PCR24 strategy, and genotypes were linked to strain-specific DNA barcodes to allow pooling and strain identification. High throughput pool barcode sequencing at different time points allowed determination of a drug by strain resistance profile, creating a profiled engineered population.

**Figure 2.** Exploring multi-knockout fitness landscapes within groups of 6-gene knockouts.

**A** A linear landscape of resistance to fluconazole, benomyl, and mitoxantrone in the MAT**a** pools. Each point represents a group of strains containing the 6-locus genotype indicated by the colour code on the right. Strains in each group vary at the remaining 10 loci. Groups are arranged horizontally by the number of knockouts (with jitter added for visual clarity), and vertically by mean drug resistance. Groups separated by single knockouts are connected – those with significant differences in resistance (Bonferroni-adjusted p < 0.05, Mann-Whitney U test) by solid lines, and otherwise by dashed lines. Representations for all pools are available in Fig. S6.

**B** A radial fitness landscape in fluconazole showing all multi-knockout paths. Each graph is centred by the 6-locus wildtype group, and concentric extensions represent further knockouts. Each section represents the mean resistance of a 6-locus group. Genotypes of outwardly connected concentric sections differ by the addition of the labelled knockout. Sections are coloured by the mean resistance of each group relative to the 6-gene wildtype (black for reference), and the colour scale extends in both directions by the largest observed difference in resistance between the 6-gene wildtype and any other group (blue in the positive direction, orange in the negative direction). All paths where any further knockouts do not result in significant changes in drug resistance (Bonferroni-adjusted p < 0.05, Mann-Whitney U test) are pruned. The inset highlights the resistance path of sequential *ybt1∆, yor1∆*, *snq2∆*, *ycf1∆*,and *pdr5∆* knockouts in the MATa fluconazole pool.

**C** As in B, showing radial fitness landscapes for 10 additional drugs.

**D** Distribution of fluconazole resistance amongst all *ybt1∆,* *yor1∆*, *snq2∆, ycf1∆,* and *pdr5∆* knockout groups in the MATa pool. Group genotype is indicated on the sides using the same representation as in A), and *pdr5∆* groups are paired with their corresponding *PDR5* equivalent in each line. The density of the resistance distribution in each group is drawn on each line.

**Figure 3.**  Formalizing and interpreting surprising multi-gene knockout phenotypes.

**A** A linear model was used to formally determine significant gene knockout and genetic interaction effects mediating resistance to the tested drugs. Linear model terms which were significant (Bonferroni adjusted p < 0.05) in both MAT**a** and MAT**α** pools for their given drug are coloured according the legend on the left. Other terms are coloured in grey. Coefficents are sorted by the number of genes involved, as indicated by the colour code on the left.

**B** Linear models and multi-knockout fitness landscapes were interpreted into a drug-dependent model of transporter-transporter relationships. Antagonism indicates evidence that the presence of one transporter negatively affects the ability of another to mediate drug resistance, and parallel clearance indicates evidence that multiple transporters are responsible for resistance to a drug. Data S8 lists the genetic evidence for each relationship.

**Figure 4.** XX Under construction. (Meant to show validation for the fluconazole experiment).

**Figure S1.** Analysis of genotyping data.

**A** Estimates of per-gene genotyping accuracy at the 16 ABC transporters surveyed. Accuracy was estimated by evaluating the performance of the *en masse* genotyping procedure on a set of known reference strains (Methods, Data S2).

**B** Tests of gene linkage within the MAT**a** (upper triangle) and MAT**α** pools (lower triangle). The Pearson correlation coefficient of the corresponding genotype pairs are indicated on the right. Pairs without significant correlation (Bonferroni-corrected p value > 0.05) are indicated in grey.

**C** Distribution of knockouts in the combined MAT**a** and MAT**α** pools. Observed number of strains with a given number of knockouts are indicated in grey, and the expected number of strains with a given number of knockouts at 93.8% genotyping accuracy under a random assortment model are indicated in black.

**Figure S2.** Correlation of fitness estimates from UP and DN tag counts.

**A** Correlation of resistance estimates in the MAT**a** pool under each drug obtained using UP tag counts (x-axis) compared to those obtained by DN tag counts (y-axis). Strains missing either a mapped UP or DN tag were excluded from the analysis.

**B** As in A), using data from the MAT**α** pool.

**C** Comparing UP and DN tag correlation with pool variability in resistance (as ). Minimum from UP and DN tag estimates is plotted for each pool.

**Figure S3.** Reproducible marginal gene knockout resistance effects in the pool.

A linear model was used to formally determine significant gene knockout effects mediating resistance to the tested drugs. Linear model terms which were significant (Bonferroni adjusted p < 0.05) in both MAT**a** and MAT**α** pools for their given drug are coloured according the legend on the left. Other terms are coloured in grey.

**Figure S4.** Reproducibility of marginal linear models.

For each drug, linear model predictions of drug resistance are indicated on the y-axis and observed values are indicated on the x-axis. The axis in each plot is labelled by the pool mating type which was used to train the linear model (x-axis) or validate its predictions (y-axis).

**Figure S5.** Profiles of grouped genotype data.

Strains were grouped on knockout genotypes at *pdr5∆, snq2∆, ybt1∆, ycf1∆,* and *yor1∆*. Each section in the heatmap represents the average resistance of strains with the genotype indicated on the y-axis, grown in the pool indicated on the x-axis. Pools are arranged by hierarchical clustering of the grouped resistance data using complete linkage.

**Figure S6.** A linear landscape of resistance to 16 drugs.

**A** A linear landscape of resistance to all tested drugs in the MAT**a** pools. Each point represents a group of strains containing the 6-locus genotype indicated by the colour code on the right. Strains in each group vary at the remaining 10 loci. Groups are arranged horizontally by the number of knockouts (with jitter added for visual clarity), and vertically by mean drug resistance. Connections are drawn between groups separated by single – those with significant differences in resistance (Bonferroni-adjusted p < 0.05, Mann-Whitney U test) by solid lines, and otherwise by dashed lines.

**B** As in A), with values shown for the MAT**α** pool.

**Figure S7.** A radial fitness landscape in six additional drugs.

A radial fitness landscape in six drugs showing all multi-knockout paths. Each graph is centred by the 6-locus wildtype group, and concentric extensions represent further knockouts. Each section represents the mean resistance of a 6-locus group. Genotypes of outwardly connected concentric sections differ by the addition of the labelled knockout. Sections are coloured by the mean resistance of each group relative to the 6-gene wildtype (black for reference), and the colour scale extends in both directions by the largest observed difference in resistance between the 6-gene wildtype and any other group (blue in the positive direction, orange in the negative direction). All paths where any further knockouts do not result in significant changes in drug resistance (Bonferroni-adjusted p < 0.05, Mann-Whitney U test) are pruned.