The adaptive potential of the middle domain of yeast Hsp90

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Abstract (up to 250 words, currently 249)

Comparing the distribution of fitness effects (DFE) of new mutations across different environments quantifies the potential for adaptation in a given environment and its cost in others. So far, results regarding the cost of adaptation across environments have been mixed, and there were no sufficiently large data sets to map its variation along the genome. Here, we study the DFEs of ≈ 2300 amino-acid changing mutations obtained from deep mutational scanning of 119 amino acids in the middle domain of heat-shock protein Hsp90 in five environments and at two expression levels. This region is known to be important for client binding, stabilization of the Hsp90 dimer, stabilization of the N terminal-Middle and Middle-C terminal interdomains, and regulation of ATPase-chaperone activity. Interestingly, we find that fitness correlates well across diverse and stressful environments, with the exception of one environment, diamide. Consistent with these results, we find very little cost of adaptation; on average only one in seven beneficial mutations is deleterious in another environment. We identify a hotspot of beneficial mutations in a region of the protein that is located within an allosteric center. The identified protein regions that are enriched in beneficial, deleterious, and costly mutations coincide with residues that are involved in the stabilization of Hsp90 interdomains and stabilization of client binding interfaces, or residues that are involved in ATPase chaperone activity of Hsp90. Thus, our study yields information

regarding the role and adaptive potential of a protein sequence that complements and extends

known structural information.

Introduction

The distribution of fitness effects (DFE) describes the proportions of new mutations that are

beneficial, deleterious or neutral (Eyre-Walker & Keightley 2007, Loewe 2010, Bataillon &

Bailey 2014). It provides a snapshot of the robustness of the genome to changes in the DNA

and carries information about the expected amount of genetic diversity within populations.

Moreover, the beneficial part of the DFE informs on the adaptive potential of populations

when introduced in a new environment (Sniegowski & Gerrish 2010, Bataillon & Bailey

2014). While maintaining the same shape of the DFE, beneficial mutations in one

environment can be deleterious in another (Bataillon et al 2011). So far, it has been difficult

to address the prevalence of such costs of adaptation (also termed antagonistic pleiotropy),

because it was difficult to measure the fitness of the same mutations across various

environments (but see, e.g., Hietpas et al 2013, Sane et al 2018).

Around a decade ago, inference of the complete DFE of a focal genomic region in several

model species started to become feasible, using a combination of site-directed mutagenesis

and deep sequencing (Fowler et al. 2010, Hietpas et al 2011, 2012, Boucher et al. 2014).

These studies usually reported a bimodal DFE with two peaks that represent neutral (or wild-

type like) mutations and strongly deleterious mutations, respectively (Acevedo et al 2014,

Bank et al 2014, Boucher et al 2014). With improvements of experimental and sequencing

technologies, studies of hundreds of thousands of mutant effects have become feasible

(Melamed et al 2013, Boucher et al 2014, Doud et al 2016, Sarkisyan et al 2016). However,

few studies have quantified the impact of environmental challenges on the shape of these

DFEs (but see Hietpas et al 2013). That is partly because inferring the adaptive potential

across environments and the cost of beneficial mutations in alternative environments requires

a high experimental resolution of selection coefficient estimates.

Experimentally quantifying the DFE across environments is important because natural

environments can change due to the alterations of abiotic factors including temperature,

salinity, and pH, which can have diverse evolutionary consequences that are directly related

to the shape of the DFE (Dhar et al. 2011, Arribas et al. 2014, Mumby and van Woesik 2014,

Brennan et al. 2017). Because environments are in general likely to change faster than

genetic adaptation can proceed, the long-term fitness of individuals depends on their ability

to deal with a wide range of environmental stresses.

Environmental challenges manifest at many biological levels, including the protein level. For

example, increased temperature can cause protein unfolding and aggregation, which can

disrupt function and ultimately affect organismal fitness and survival (Richter et al. 2010).

Chaperones, such as the heat shock protein Hsp90, help the cellular machinery survive stress

conditions (Chen et al. 2018). They are an important line of defense for new and recurring

environmental challenges and can also function to increase standing genetic variation that can

facilitate adaptation to new stress conditions (Barrett and Schluter 2008, Jarosz and Lindquist

2010, Fitzgerald and Rosenberg 2019). Therefore, it is important to understand how

chaperones themselves evolve, and how the selection pressure on the chaperone changes

upon exposure to different environmental challenges.

Hsp90 is a chaperone that plays an essential role in protecting cells from environmental stress

and that is required at elevated levels for yeast growth at high temperature (Borkovich et al.

1989). Under optimal conditions Hsp90 can suppress the phenotypic consequences of

mutations in signal transduction pathways by correctly folding mutant clients (Sangster et al.

2004, Jarosz and Lindquist 2010, Zabinsky et al. 2019). However, in stressful conditions

there is an increase in the concentration of stress-induced unfolded and damaged proteins,

which compete for Hsp90 chaperone function (Sangster et al. 2004, Taipale et al. 2010).

Thus, mutations in protein clients and in Hsp90 itself may have environment-dependent

phenotypic and ultimately fitness consequences.

Recent studies using systematic mutagenesis have begun to address how mutations to a

strongly conserved client binding site of Hsp90 can impact evolutionary adaptation in yeast

(Hietpas et al. 2013). Multiple mutations in a nine amino acid client-binding site of yeast

Hsp90 provided a growth advantage under elevated salinity conditions (Hietpas et al. 2013,

Bank et al 2014). A recent larger-scale study found that at low Hsp90 expression levels,

changes in environment greatly changed the shape of the DFE, and that some environments

showed a higher prevalence of both beneficial and deleterious mutations (Flynn et al 2019).

However, another previous study proposed that at low expression the fitness effects of

mutations, especially deleterious ones, should be larger (Jiang et al 2013). Thus, it is

unknown how much of the observed effect was due to expression level and how much was

due to environmental changes.

Here we examined a 119 amino acid region (encompassing positions 291-409, Fig. 1) of the

middle domain of yeast Hsp90 (aka Hsp82) at normal expression levels. Several studies have

demonstrated that the middle domain of Hsp90 plays a prominent role in client binding

(Nathan and Lindquist 1995, Nathan et al. 1997, Meyer et al. 2003, Hawle et al. 2006, Hagn

et al. 2011), and suggested that mutations in this region may impact the relative affinity or

priority of different clients and physiological pathways with the potential to provide an

adaptive benefit (Hagn et al. 2011, Zhang et al. 2005, Sato et al. 2000, Karagoz et al. 2014,

Verba et al. 2016, Czemeres et al. 2017).

Figure 1: **Middle domain of Hsp90**

(A) Structural representation based on 1HK7.PDB of the middle domain of Hsp90, with

amino acids 291-409 that are the focus of this study highlighted in purple. A solvent exposed

amphipathic loop implicated in client binding (amino acids 327-341) is highlighted in yellow

and residues implicated in client binding (amino acids W300, F329, F349) are shown as gray

sticks. (B) Alignment of amino acids 291-409 of yeast Hsp90 with human Hsp90. Boxed in

red are amino acid residues implicated in client binding. Amino acids are colored based on

their chemical properties.

We used the EMPIRIC approach of deep mutational scanning (Hietpas et al 2011) to estimate

the selection coefficient of all amino-acid changing mutations in the middle domain of yeast

Hsp90 across five environments. Whereas the present study was performed at normal

expression levels, we included low-expression data from Flynn et al. 2019 in diamide, salt

and standard conditions in our analysis to evaluate the impact of protein expression on the

fitness effect of mutations. Using the inferred DFEs, we identified regions of the middle

domain that stand out with respect to their potential for adaptation upon environmental

change. To this end we: a) quantified the impact of environmental changes on the overall

shape of the DFE, b) identified regions that show the largest proportions of beneficial or

deleterious mutations, respectively, c) quantified hotspots of costs of adaptation, and d)

compared the identified regions with known client binding or other structurally important

sites to connect the phenotypic and fitness effects of mutations.

Results and Discussion

Deep mutational scanning across environments and expression levels reveals distributions of fitness effects. To investigate the adaptive potential of the middle domain of yeast Hsp90 we used systematic site-directed mutagenesis of amino acid positions 291-409 that include known client binding sites. This resulted in ≈2300 amino-acid changing mutations, whose selection coefficients were estimated from 2-3 replicates of bulk competitions that were performed in five environments. We focused our analysis on standard lab conditions and four environmental stresses that affect both growth rate (Supplementary figure 1) and the adaptive gene expression response in yeast (Gasch et al. 2000). Two environments caused osmotic stress (0.5M salinity or 0.6M sorbitol) and two caused oxidative stress (0.6 mM H202 or 0.85mM diamide). These conditions were chosen because of the role of Hsp90 in yeast response to these environmental stressors. In yeast, responses to environmental stress require changes in signaling pathways that dramatically alter gene expression programs (de Nadal et al. 2011). For example, during osmotic stress, Hog1, the yeast homolog of the mammalian p38 mitogen activated protein kinase, becomes activated (Hawle et al., 2007) and results in the induction of ~600 genes (Westfall et al. 2004). Hsp90 function is required for adaptation to osmotic stress (Yang et al. 2006) and Hsp90 is necessary for the activation of the HOG pathway (Hawle et al. 2007, Yang et al. 2007). Although Hsp90 function is required for the osmotic stress response, increased expression of Hsp90 does not occur in this condition (Gasch et al. 2000). In contrast, the oxidative stresses of diamide and H_2O_2 cause an increase in the expression of chaperones, including Hsp90 (Gasch et al. 2000). Moreover, while each of these conditions causes changes in the expression of ~900 genes, diamide and H_2O_2 stress promote similar gene expression responses to those observed during thermal stress in yeast (Gasch et al. 2000). To allow for comparisons of mutational fitness across expression levels (Dekel and Alon 2005, Manceau et al. 2011), we included three data sets that were obtained in previous work (Flynn et al. 2019), which evaluated the same mutations at constitutively low expression levels in the standard lab environment, the high-salinity environment, and the diamide environment.

DFEs across all environments show many wild-type like mutations. The shape of the
DFE indicates the relative importance of purifying or directional selection as compared with
neutral evolution. In apparent contrast to the strong conservation of the Hsp90 middle domain
in natural populations, we observed DFEs with mostly wild-type like mutations across all
environments (Supplementary Figure 2, 3). Here, we categorized mutants as wild-type like if
the 95% confidence interval of the estimated selection coefficient overlapped with 0 (see also
Supplementary Table 1, Materials & Methods). According to this criterion, at high expression
levels, between 50% (in the H_2O_2 environment) and 65% (in the standard environment) of
mutations showed a fitness effect that is indistinguishable from the reference type. At low
expression levels, where the experimental resolution was lower, between 63% and 73% of
mutations (in the standard and diamide environments, respectively) showed a wild-type like
effect. Large numbers of wild-type like mutations have been observed previously in deep
mutational scanning studies of DFEs (Soskine and Tawfik 2010, Hietpas et al 2013, Melamed
et al 2013, Bank et al 2014, Hom et al 2019). Both biological and technical factors can be
invoked as an explanation for the large number of wild-type like mutations. Firstly, the
resolution of the experiment is likely much lower than the resolution at which natural
selection may occur in large yeast populations (Ohta 1992, Boucher et al. 2016). Secondly,
selection pressures in the laboratory might differ greatly from those in nature (e.g., Reznick
& Ghalambor 2005, Kvitek and Sherlock 2013). Finally and relatedly, natural environments
might be fundamentally different and rapidly fluctuating (Mustonen and Lässig 2009). For
example, a recent study of the DFE of the full Hsp90 sequence found that mutations that were
tolerated across a set of diverse environments were those most likely observed in natural
sequences (Flynn et al., 2019).

Correlations across conditions reveal that diamide stands out with respect to mutational effects. We next quantified the correlations of fitness effects across replicates, environments and expression levels (Figure 2, Supplementary Table 2). Consistent with the high accuracy of the experiment, we observed strong correlations between replicates (mean Pearson correlation r=0.91). Across environments and expression levels, we observed a large variation of correlations ranging from r=0.36 between diamide and low-expression salt to r=0.98 between H_2O_2 and the standard environment. In this analysis, diamide clearly stood out by showing consistently lower correlations with other environments and expression levels than all others (mean correlation including diamide r=0.64, mean correlation of all others r=0.83). This could be because diamide exerts multiple negative effects on the yeast cells. For example, among the environments we investigated, diamide was the only condition that induces the expression of cell wall biosynthesis genes and genes involved in protein secretion and processing in the Endoplasmic Reticulum, which indicates its role in cell wall damage (Gasch et al. 2000). Diamide was also shown to affect individual transcription factors differently from H_2O_2, the other oxidizing environment in our selection. For example, the Yap1 transcription factor is nuclear localized and active in diamide, but cytoplasmic and inactive in H_2O_2 (Gulshan et al. 2011). Further analyses will be required to determine the molecular features of diamide stress that elicit distinct selection on Hsp90 sequence.

Figure 2: **Histogram of correlations of fitness effects among replicates, expression levels, and environments reveals that diamide stands out as different.** The histograms correspond to comparisons of replicates (A), expression levels (B), comparisons that include diamide (C), and all other comparisons (D). Correlations between replicates and between several environment pairs are in general high, whereas correlations between diamide and the other environments tend to be lower. Correlations between the same environment at different expression levels vary, with diamide showing the lowest correlation between expression levels (see also Supplementary Table 2). Altogether, this suggests that cells react in unique ways to the oxidative stress enacted by exposure to diamide, and that Hsp90 plays a large role in the response to this stress.

We also observed a tendency for larger correlations of selection coefficients from the same batch of experiments (Supplementary Table 2). Therefore, we performed some of the analyses (as indicated below) using the average of the estimated fitness effects between replicates and re-categorizing mutations based on the mutant category of both replicates (see also Materials and Methods).

Finally, we compared the correlations of fitness effects across environments with those from

the same environment, but obtained at a different (constitutive) expression levels. A general

expectation is that the Pearson correlation of DFEs between different expression levels

should on average be larger than between environmental conditions. This would be consistent

with the results and the model of Jiang et al. 2013, who showed that the variance of the DFE

increases at lower expression level. That is expected because at lower expression, protein

function and fitness become more directly related such that small functional effects should

become more visible to growth analyses. However, we see only small differences in the mean

correlations within environments at the same expression level compared with correlations

between expression levels (mean Pearson correlation across expression levels: r=0.76, vs.

r=0.78 for correlations of environments with the same expression level). Again, we find that

diamide stands out with a particularly low correlation between low and normal expression

levels. This makes sense with respect to the above-mentioned arguments, because an increase

in Hsp90 expression levels is required to maintain protein and cellular homeostasis under

diamide conditions (Gasch et al. 2000), which is compromised when Hsp90 is expressed at

lower levels.

The large correlations observed between most environments suggest that potential costs of

adaptation (discussed in detail further below) should be the exception rather than the rule.

This is at odds with previous results from a smaller region of Hsp90 (Hietpas et al 2013),

where most beneficial mutations detected at high salinity were deleterious in other

environments. A potential explanation for this discrepancy lies in the choice of the protein

region. Whereas the previous study focused on only nine amino acids and thus chose a set of

positions that are likely to show functionally interesting patterns, we here had the

experimental power to scan a larger region of the protein. Along a larger, less specifically

chosen, stretch of the protein, it is likely that many positions and mutations play the same

role across many environments. Consequently, only a small number of mutations in this

greater set may have a functionally different role across environments, leading to costs of

adaptation. In such cases, costs of adaptation of beneficial mutations could still be large, but

due to their low proportion they barely affect the correlation of selection coefficients across

environments.

255   **Beneficial mutations appear across all environments and are enriched in a region of**

256   **Hsp90 that is implicated in stabilization of interdomains and client binding interfaces.**

Next, we identified the proportion and identity of putatively beneficial mutations across all

treatments (Supplementary Table 1, Supplementary Figure 4, 5). We categorized mutants as

putatively beneficial if the lower limit of the 95% confidence interval of the selection

coefficient was larger than 0, and we considered as strongest candidates those that overlapped

between replicates from the same environment. As reported above, wild-type like mutations

are the most abundant category in all environments, with a low proportion but considerable

number of beneficial mutations in almost all environments (Supplementary Figure 4, 5). We

find the lowest number of beneficial mutations in H_2O_2 and salt environments (n_{H2O2}=65 and

n_{Salt}=64, around 2.5% of the mutations) and the highest in diamide ($n_{Diamide}$=307, 12.3%).

Interestingly, in diamide beneficial mutations were dispersed across the whole middle

domain (Supplementary Figure 4), whereas most of the other environments showed a clear

enrichment of beneficial mutations in the region of positions 356-366 (Figure 3,

Supplementary Figure 4). This hotspot of beneficial mutations was particularly strong in

sorbitol (Supplementary Figure 4). Out of the 31 beneficial mutations that show a beneficial

effect in at least two environments, 18 are located in this hotspot.

Figure 3: **Hotspots of beneficial and deleterious mutations in the middle domain do not**

coincide with known client binding loop. A) Average proportion of beneficial and

deleterious mutations along the genome across all environments, illustrated using a 10-

amino-acid sliding window. The region with the 10% largest proportions of beneficials is

highlighted in light orange (position 356-366), the region with the 10% largest proportions of

deleterious mutations is highlighted in light blue (positions 347 and 376-385). A known

client binding loop (positions 327-341) is highlighted in light gray. To avoid biases, the

analysis was restricted to subsets of two replicates of all normal-expression environments. B)

The beneficial hotspot is adjacent to a known client binding loop. Structural representation

of the Hsp90 middle domain (1HK7.PDB) illustrating the beneficial hotspot in magenta with

residue 364 highlighted in cyan. Biochemical, structural and mutational studies identified

positions 327-341 as a client binding loop, which is shown in blue. C) The deleterious

hotspot contains a catalytic amino acid and is at a dimerization interface. Structural

representation of the ATPase and middle domains of Hsp90 from 2CG9.PDB. The

deleterious hotspot is colored in cyan and includes R380 that stabilizes the leaving phosphate

during ATP hydrolysis. Subunits are distinguished with different shading. D) The deleterious

hotspot at position 347 is also located at the interface of the ATPase domain and the middle

domain, and is highlighted in pink and blue.

Interestingly, the beneficial hotspot contains residues that are part of an allosteric center

which mediates distinct conformations in structures with and without client (Czemeres et al.

2017). Despite its different structural arrangements, the hydrophobic amino acids in this

region are mostly buried from solvent (Figure 3B), indicating that the primary role of this

region is to mediate the stability and rearrangement of different conformations. Of note, the

position with the greatest number of beneficial mutations is F364 (Supplementary Figure 6).

The burial of the large hydrophobic side chain of F364 should provide local stability. The

beneficial mutations at position 364 and in this region in general suggest that disruption of

local stability and conformational dynamics may alter Hsp90 function. Based on the

prominent role of the middle domain in binding to clients, we hypothesize that Hsp90

function may be altered by the identified candidate beneficial mutations in a manner that

changes the relative affinity and thereby priority of different clients - a property that could

provide benefits in specific conditions. Consistent with this hypothesis, the beneficial hotspot

is adjacent to a known client binding loop (Figure 3) such that alterations in the structure or

dynamics of the hotspot are likely to influence client binding nearby. It is possible that

natural selection balances client priorities integrated over multiple conditions, which provides

opportunities for Hsp90 mutations to improve priorities for individual conditions.

The proportion of deleterious, wild-type like, and beneficial mutations varies greatly along the protein sequence. We showed above that the correlations of fitness effects across environments are generally large, which indicates similar effects of the same mutations across environments. In contrast, the proportions of beneficial, wild-type like, and deleterious mutations vary greatly along the protein sequence. Whereas the overall pattern is similar between environments, the relative proportions differ between environments (Supplementary Figure 4, 5). For example, at low expression there are less beneficial mutations, but the regions that show deleterious mutations are similar between expression levels (Supplementary Figure 4). Our finding that the same positions are enriched for deleterious and beneficial mutations across environments suggests that the structural properties of the middle domain in these regions, rather than its binding partners, might be the most important factor for predicting the fitness effects of mutations.

One position that particularly stands out with respect to the proportions of beneficial, wild-type like and deleterious mutations is 364. Position 364 lies at the center of the cluster of the 10% largest average proportions of beneficial (Figure 3B) and shows a clear deviation from the usually observed DFE with an enrichment of beneficials (Supplementary Figure 6). Specifically, we identified 6 mutations at this position that are beneficial in at least two environments (Supplementary Figure 6) . As mentioned above this may be due to a disruption of the stability of the protein that may alter the relative affinity of Hsp90 to its clients, which may be beneficial in specific environments.

Interestingly, the regions with the largest proportions of deleterious mutations are located near the ends of the beneficial hotspot region (position 347 and 376-385, respectively) (Supplementary Figure 4). At the latter deleterious hotspot, around 70% of all mutations are deleterious in a sliding window of 10 amino-acid positions. Such a shift of the DFE towards deleterious mutations suggests that this protein region is under strong purifying selection. Structurally, the region 376-385 is part of a catalytic loop required for ATP hydrolysis which is necessary for the activation of all known clients (Wolmarans et al. 2016). Position R380 in the catalytic loop binds to and stabilizes the leaving phosphate of ATP (Figure 3C) and mutations at this position compromise Hsp90 function and cell viability (Meyer et al.2003). The efficiency of catalysts depends strongly on geometry, and the precise location of R380 relative to ATP is likely tightly linked to Hsp90 function. The regions adjacent to R380

appear to be important for positioning the catalytic arginine, providing a rationale for the

strong purifying selection that we observe. The other deleterious hotspot at position 347 is

also located at the interface of the ATPase domain and the middle domain (Figure 3D),

consistent with current understanding that Hsp90 mechanism requires precise ATP-dependent

interactions between these domains (Schopf et al. 2017).

Few mutations show costs of adaptation. Among the identified beneficial mutations, we

were specifically interested in those that are deleterious in other environments, which results

in a so called "cost of adaptation". The same phenomenon has also been termed antagonistic

pleiotropy. In previous work we reported a large prevalence of costs of adaptation in a 9-

amino-acid region of Hsp90 (Hietpas et al 2013). In this study, we found that costs of

adaptation are not pervasive (Figure 4, Supplementary Table 3). Consistent with the

comparatively low correlations of fitness effects and the special role of the diamide stress

discussed above, we observed the largest proportion of mutations that show costs of

adaptation between diamide and other environments. Whereas the mean proportion of

mutations displaying costs of adaptation across all comparisons of environments was 14.3%,

comparisons that included diamide showed on average 22.7% mutations with costs of

adaptation. The largest proportions of mutations with costs of adaptation (>40%) were seen

in comparisons of low-expression diamide and high-expression H_2O_2.

Figure 4: Histogram of proportions of mutations that display costs of adaptation

illustrates that costs of adaptation are generally rare, and most likely if comparisons

involve diamide environments. The histograms correspond to comparisons of replicates

(A), expression levels (B), the subset of other comparisons that include diamide (C), and all

other comparisons (D). There is an enrichment of mutations that show costs of adaptation in

comparisons between all environments and diamide, compared to comparisons between

replicates, expression levels and other environments. This is consistent with what was

observed above and further supports that the stress through exposure to diamide is different

from all other environments.

Mapping the proportion of beneficials that are deleterious in other environments along the

protein sequence, we observed that there is a hotspot for costs of adaptation at amino-acid

positions 381-391 (Figure 5). Interestingly, this region showed costs of adaptation across

various environments, which indicates that each environment has specific beneficial

mutations that are deleterious in other environments. Structurally, this region also belongs to

the catalytic loop involved in ATP hydrolysis discussed above. Indeed, the identified region

partly overlaps with the above-discussed hotspot of deleterious mutations (positions 376-

385), which is unsurprising since a larger proportion of deleterious mutations also increases

the (technical) proportion of mutations that can be classified as costly.

Figure 5: A hotspot of costs of adaptation is located at positions 381-391. The 10%
positions with the largest mean proportion of mutations that display costs of adaptation (dark
purple line) are highlighted in light purple. This region greatly overlaps with the hotspots of
deleterious mutations from Figure 3 (highlighted in blue). Thin curves indicate the mean
proportion of beneficial mutations in a focal environment that is deleterious in another
environment. A 10-amino-acid sliding window was used to locate region-specific effects. To
avoid biases, the analysis was restricted to subsets of two replicates of all normal-expression
environments.

We next computed whether there was a correlation between the effect of beneficial mutations
in one environment with their effect in the other environments. Indeed, the effects of
beneficial mutations in diamide are negatively correlated with the same mutation's effect in
all other environments (Figure 5, Supplementary Figure 7) except H_2O_2. In other words, the
more beneficial a mutation was in diamide, the more deleterious tended to be in salt, standard
and sorbitol. Again, this suggests that the beneficial mutations we identified in diamide may
be involved in the response to a very specific type of stress. Across all other environments,
we did not see any evidence that stronger beneficial mutations tended to have a more
deleterious effect in other environments.

Conclusion

Recent advances in experimental and technological approaches have led to the feasibility of large-scale screens of the DFE of new mutations, which, from an evolutionary point of view, is a key entity to determine the potential for adaptation. Here, we took a new route by mapping the proportions of beneficial, wild-type like, and deleterious mutations along a 119-amino-acid region of the Hsp90 protein in yeast, a protein that is heavily involved in the response to environmental stressors. By comparing the DFE along the protein sequence and between environments, we identified hotspots of beneficial and deleterious mutations that are common across environments, and a region in which beneficial mutations in one environment tend to be deleterious in other environments. Interestingly, neither of these regions coincided with the best described client binding loop in the studied region, which we had *a priori* considered the most likely candidate to display patterns different from the rest of the region. Moreover, our analyses suggested that mutational effects generally differ little across environments except in diamide, which stands out both with respect to the number and also the distribution of beneficial mutations along the studied protein region. Altogether, our study of the DFE across environments sheds light on the evolutionary role of a specific protein region from a new perspective.

Materials and Methods

Generating point mutations. To accurately measure the fitness effects of all possible point mutations in a large portion of the middle (client-binding) domain of yeast Hsp90, we used saturation mutagenesis at positions 291-409 (see Supplementary figure 8). We used a cassette ligation strategy to introduce mutations as previously described (Hietpas et al. 2012). This strategy reduces the likelihood of secondary mutations because it avoids the potential for errors during PCR steps. As a control for the mutational procedure, twelve positions were randomized in isolation and Sanger sequenced to assess the level of incorporation of all four nucleotides at each position in the target codon. At all randomized nucleotide positions within these twelve samples, we observed a similar magnitude of signal for each of the four nucleotides. For larger scale production, libraries were generated at 10 positions at a time as previously described (Hietpas et al. 2012). As additional controls, we generated a sample containing individual stop codons as well as the parental wildtype Hsp90 sequence. All variants of Hsp90 were generated in a plasmid (pRS414GPD) previously shown to produce endogenous levels of Hsp90 protein in yeast (Chang and Lindquist 1994).

Constructing barcoded libraries. To improve the efficiency and accuracy of fitness
estimates, we added barcodes to a non-functional region of the plasmid, ~200 NTs
downstream from the 3' untranslated region of Hsp90. Barcodes were introduced using a
cassette ligation strategy (Supplementary Figure 8). Plasmid libraries were treated with NotI
and AscI to generate directional sticky ends. NotI and AscI recognize 8-base cut sites that are
unlikely to cut any of the Hsp90 variants in the library. We designed and annealed barcode
forward and barcode reverse oligos together such that the resulting duplex product included a
central N18 region bracketed by constant regions that facilitate annealing and overhangs that
direct directional ligation into NotI and AscI overhangs. One of the constant ends in the
designed oligo cassette contains an annealing region for an Illumina sequencing primer.
Barcoded libraries were transformed into *E. coli* and pooled into a bulk culture that contained
about 10-fold more transformants than Hsp90 variants in the library. We purified barcoded
plasmids from this bulk culture. This procedure resulted in approximately 10 barcodes for
each Hsp90 codon variant in the library (Supplementary Figure 9). The potential diversity in
the N18 barcode that we used ($4^{18} \sim 10^{11}$) far exceeds the number of barcodes that we utilize
($\sim 64*119*10 \sim 10^5$), which makes it likely that each Hsp90 variant will have a barcode that
differs from all other barcodes at multiple nucleotides. With this setup, errors in sequencing
of barcodes can be detected and eliminated from further analysis, which reduces the impact
of sequencing misreads on estimates of variant frequency and fitness. Additional controls
consisting of individual stop codons and wildtype Hsp90 were barcoded separately. For these
controls, we isolated barcoded plasmid DNA from individual bacterial colonies and
determined the barcodes by Sanger sequencing (Supplementary Figure 8).

Associating barcodes to mutants. To identify the barcodes associated with each Hsp90
variant in our libraries, we used a paired-end sequencing approach essentially as previously
described (Hiatt et al. 2010, see also Supplementary Figure 10). Using paired-end
sequencing on an Illumina MiSeq Instrument barcodes were associated with variant
genotypes via reading from the Hsp90 gene with a 250 base-pair read and the associated N18
barcode with a 50 base-pair read. To reduce the size of the DNA fragments for efficient
Illumina sequencing, we removed a portion of the Hsp90 gene such that the randomized
regions were closer to the N18 barcode. This was done to increase the density of DNA on the
sequencer by reducing the radius of clonal clusters during sequencing. Plasmid DNA was
linearized with StuI and NotI endonucleases that removed ~400 bp's of DNA. The linearized

products were circularized by blunt ending followed by ligation at DNA concentrations that

predominantly lead to unimolecular ligations (Revie et al 1998) . The resulting DNA

products were amplified using a PE2_F primer and the standard Illumina PE1 primer that

anneals next to the N18 barcode. Two PE2_F primers were designed in order to read across

the region of Hsp90 that we randomized. PCR products were gel purified and submitted for

paired end sequencing. We obtained sufficient paired-end reads such that the average barcode

was read more than 10 times. The paired-end sequencing data was subjected to a custom data

analysis pipeline to associate Hsp90 variants with barcodes. First, very low-quality reads with

any Phred score less than 10 in reads 1 or 2 were discarded. Next, the data were organized by

the barcode sequence. For barcodes with three or more reads, we constructed a consensus of

the Hsp90 sequence read. We compared the consensus sequence to the parental Hsp90

sequence in order to determine mutations. Consensus sequences containing more than one

protein mutation were discarded. The pipeline output generated a file organized by point

mutation that lists all barcodes associated with that mutation (Supplementary Data). This file

was used as the basis for calling a variant based on barcode reads.

Yeast competitions. As in previous work (Hietpas et al. 2012, Hietpas et al. 2013), we

performed Hsp90 competitions using a shutoff strain of *S. cerevisiae* (DBY288) (

Supplementary figure 11). The sole copy of Hsp90 in DBY288 is driven by a galactose-

inducible promoter, such that the strain requires galactose for viability and cannot grow on

glucose. The introduction of a functional Hsp90 variant driven by a constitutive promoter

rescues the growth of DBY288 in glucose media. We introduced the library of middle

domain variants of Hsp90 driven by a constitutive promoter into DBY288 cells using the

lithium acetate method (Gietz and Schiestl 2007). The efficiency of transformation was more

than 10-fold higher than the number of barcodes, such that the average barcode was

transformed into more than 10 individual cells. To enable the analyses of full biological

replicates, transformations were performed in replicate such that a separate population of

yeast were transformed for each biological replicate. Transformed yeast were initially

selected in RGal-W (synthetic media that lacked tryptophan and contained 1% raffinose and

1% galactose supplemented with 100 μg/mL ampicillin to hinder bacterial contamination) to

select for the plasmid, but not function of the plasmid encoded Hsp90 variant. This enabled

us to generate a yeast library containing Hsp90 variants that could support a full range of

fitness from null to adaptive. Cells were grown for 48 hours at 30 °C in liquid SRGal-W until

the culture was visibly opaque compared to a control transformation sample that lacked

plasmid DNA but was otherwise identical to the library sample.

To initiate the competition, cells were transferred to shut-off conditions and different

environmental stresses. In order to deplete the pool of wild type Hsp90 protein, the library

sample was diluted into SD-W (synthetic media lacking tryptophan with 2% glucose and 100

μg/mL of ampicillin) and grown at 30 °C for 10 hours. After depletion of wild type Hsp90

protein, the cells were split into different stress conditions in SD-W media at 30 °C: salt

stress (0.5M NaCl), osmotic stress (0.6M sorbitol), oxidative stress (0.6 mM hydrogen

peroxide or 0.85 mM diamide), as well as a control non-stress condition. We used a custom

built turbidostat (Supplementary figure 11) to provide constant growth conditions during this

competition phase of the experiment. Cells were grown under consistent density and

population size. 10^9 cells were maintained in a 50 mL volume over the course of 40 hours for

each condition. Rapid magnetic stirring was used to provide aeration to the media and cells.

Samples of 10^8 cells were collected after 0, 4, 8, 12, 24, 32, 40, and 48 hours of competition

in the different conditions. At the time of collection, samples were centrifuged and the pellets

immediately frozen at -80 °C.

Sequencing of competition samples. The fitness effects of Hsp90 variants were estimated

based on frequencies observed in next-generation sequencing analyses essentially as

previously described (Hietpas et al. 2012). DNA was isolated from each timepoint sample as

described (Hietpas et al. 2013) and the barcodes were amplified and sequenced. Barcodes

were amplified using the standard Illumina PE1 primer that anneals next to the N18 barcode

and custom designed barcode_forward primers. A set of barcode_forward primers were

designed with identifier sequences that could be read during sequencing and used to

distinguish each timepoint sample. Each identifier sequence was eight nucleotides in length

and differed by at least two bases from all other identifier sequences. Twenty cycles of PCR

were sufficient to generate clear products from all samples. These PCR products were

purified on silica columns (Zymo Research) and sequenced for 100 base single reads on an

Illumina NextSeq instrument. The barcode corresponded to the first 18 bases and the

identifier at positions 91-98. The resulting fastq files were processed and analyzed using

customized software tools. First, poor quality reads containing any positions with a Phred

score less than 20 were discarded. Reads were tabulated if the barcode matched a barcode

associated with a point mutation and if the identifier matched with a timepoint. The analyses

scripts output a file with the number of reads for each amino acid point mutant at each

timepoint in each condition (Supplementary Data). Barcodes with 0 reads at the first time

point, or with a total of 1 read along the whole trajectory were removed from the analysis.

Estimation of selection coefficients. Inference of selection coefficients was performed via

log-linear regression as described in Matuszewski et al 2016 (see also Supplementary

Material). To improve estimation accuracy by incorporating information from each individual

barcode, the linear model for each amino-acid changing mutation included barcode identities

as nominal variables. For each amino-acid changing mutation we obtained a selection

coefficient and 95% confidence interval (CI) of the estimate, representing the variation within

amino acid due to differences in codon*Barcode tag throughout time. This reduces the impact

of potential outliers and averages over synonymous codons within amino acid. Mutants with

50 or less total reads at the first time point were removed from the data set. Finally, we

normalized all selection coefficients, by subtracting the median of all mutations that were

synonymous to the wild type. This ensures that the average of the selection coefficients of

wild type synonyms represents a selection coefficient of 0. To categorize mutations as

beneficial, deleterious or neutral we tested the overlap of the CI with 0. Namely, if the lower

CI limit was larger than 0, a mutation was considered beneficial, and if the upper CI limit was

smaller than 0, a mutation was considered deleterious. All other mutations were considered

wild-type like.

Costs of adaptation. To compute the costs of adaptation for Figure 4 and 5, we first selected

all mutations in a focal environment that were categorized as beneficial. We then computed

the proportion of this subset of mutations that was deleterious either in one other environment

(for Figure 4) or across all other environments (excluding replicates of the focal environment

and low-expression environments; for Figure 5). Calculating the proportion of mutations with

costs of adaptation compensates for variable numbers of beneficial mutations across

environments, which may occur due to both biological and experimental reasons (e.g.,

different error margins). For Figure 2 and 4, all available data sets were considered for the

analysis. For Figure 3 and 5, only two replicates of each environment were considered, and

the low-expression data were excluded. That was in order to avoid biases due to the under- or

overrepresentation of environments in the analysis.

Analyses were performed using R version 3.5.1 (R Core Team 2018), Mathematica 12.0.0.0,

Python 2.7.12 and Pymol 0.99. Code is available as Supplementary Material.

All data will be made available in a data repository upon acceptance of the manuscript.

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Supplementary Material

Supplementary Figures and Tables

Supplementary figure 1. Doubling times for WT Hsp90 yeast growth under all

environments. In general there is an increase in the doubling time in all environments tested

compared to the standard environment. This increase is larger in high salinity and diamide

environments, suggesting that these environments should present the highest stress load to the

protein.

Supplementary Figure 2 Distribution of Fitness Effects (DFE) across environments and expression levels. Replicates within an environment largely overlap. There is a marked difference of the DFE in diamide compared to the other environments, especially at low expression levels. Interestingly, DFEs in H_2O_2 and salt show a similar shape to the DFE in the standard environment, with a large number of mutations in the wild-type like region and a smaller peak of deleterious mutations, at which stop codons are located. In diamide and sorbitol, the DFE shows a lower number of wild-type like mutants, a larger variance, and a higher proportion of weakly and strongly deleterious mutations.

B

C

D

Supplementary Figure 3. **Heatmaps of mutant fitness effects show that the majority of**

mutations are wild type under all conditions, with the exception of amino acid regions

~300, 315-320, 347 and 375-390 that show mostly deleterious mutant fitness effects.

Beneficial mutations were found under all conditions but in different regions of the

middle domain. (A) Diamide heatmaps under low and normal expression. (B) H_2O_2

heatmaps under normal expression. (C) Salt heatmaps under low and normal expression. (D)

Sorbitol heatmaps under normal expression. (E) Standard heatmaps under low and normal

expression.

Supplementary Figure 4

Proportions of deleterious, beneficial and wild-type like mutations along the middle

domain of Hsp90. The x-axis corresponds to the amino acid positions studied and the y axis

to the proportion of deleterious, beneficial and neutral mutations at each amino acid position.

The rows indicate expression level and replicate, the columns the different environments.

Supplementary Figure 5

Summary of the proportions of beneficial, deleterious and neutral mutations in each

environment/replicate/expression level. In general we see few beneficial mutations, except

in diamide, especially at low expression. In diamide, there is also a larger proportion of

deleterious mutations in comparison with other environments.

Supplementary Figure 6

Distribution of fitness effects at position 364. Compared with the DFE of the whole middle

domain (Supplementary Figure 1), there is a clear enrichment of beneficial mutations in

position 364, especially at normal expression levels.

Supplementary Figure 7

Cost of adaptation in different environments. Each plot represents the average fitness

effect of mutations that are beneficial in a specific environment (x-axis) and the average

fitness effect in other environment (y-axis). Focal environments are indicated by the color of

the lines and points. Note that the x and y scales vary between panels. To improve

visualization, we calculated the average fitness effects between the two (or three replicates)

and mutations were recategorized based on whether mutations were beneficial in two

replicates (beneficial mutations), beneficial in one replicate and neutral in another

(beneficial-neutral), neutral in both replicates (neutral mutations), neutral in one replicate and

deleterious in the other (neutral-deleterious mutations), deleterious in both replicates

(deleterious) or deleterious in one replicate in beneficial in the other (beneficial-deleterious

mutations).

Supplementary figure 8. Barcoding mutant library strategy. (A) Schematic of how to

incorporate barcodes into plasmid libraries using restriction digests and ligation. (B) Sanger

sequence TRACE result of barcoded region of the library at positions 475-493. (C)

Schematic of how to map barcodes to ORF mutants.

Supplementary figure 9.Average number of barcodes per mutant for each 9 amino acid

window shows an average of 10 barcodes associated with each variant .

Supplementary figure 10. Strategy to prepare barcoded mutant libraries for sequencing. (A)

Schematic of how to prepare barcoded mutant libraries for paired end deep sequencing.(B)

Schematic of how to include an index primer to distinguish each time point and final

sequencing read.

Supplementary figure 11: Systematic approach to measure the adaptive potential of the

middle domain of yeast Hsp90 (amino acids 291-409).

Environment	Replicate	Expression	% Beneficial	% Neutral	% Deleterious	Total Mutations
H202	1	normal	5.03 (125)	50.2 (1248)	44.77 (1113)	2486
H202	2	normal	2.65 (65)	54.5 (1337)	42.85 (1051)	2453
Diamide	1	low	7.9 (197)	63.54 (1584)	28.56 (712)	2493
Diamide	1	normal	12.34 (307)	34.74 (864)	52.92 (1316)	2487
Diamide	2	normal	10.73 (266)	41.19 (1021)	48.08 (1192)	2479
High Salinity	1	low	3.53 (88)	72.59 (1809)	23.88 (595)	2492
High Salinity	1	normal	2.57 (64)	59.58 (1486)	37.85 (944)	2494
High Salinity	2	normal	4.85 (121)	59.34 (1480)	35.81 (893)	2494
Sorbitol	1	normal	7.09 (176)	51.37 (1276)	41.55 (1032)	2484
Sorbitol	2	normal	9.97 (245)	60.09 (1477)	29.94 (736)	2458
Standard	1	low	2.53 (63)	62.55 (1558)	34.93 (870)	2491
Standard	1	normal	9.03 (225)	65.53 (1633)	25.44 (634)	2492
Standard	2	normal	6.14 (153)	66.75 (1664)	27.12 (676)	2493
Standard	3	normal	5.19 (129)	49.6 (1232)	45.21 (1123)	2484

892 **Supplementary Table 1**

Number of beneficial, neutral and deleterious mutations across environments, expression levels and replicates. Gray cells corresponds to low expression level mutants (from Flynn et al 2019). We observed a large proportion of wild-type like mutations in all environments.

			Low Expression			Normal Expression										
						Diamide		Salt		Standard			H2O2		Sorbitol	
			Standard	Diamide	Salt	Rep1	Rep2	Rep1	Rep2	Rep1	Rep2	Rep3	Rep1	Rep2	Rep1	Rep2
Low Expression	Standard		■													
	Diamide		0.77	■												
	Salt		0.88	0.70	■											
Normal Expression	Diamide	Rep1	0.61	0.61	0.51	■										
		Rep2	0.48	0.50	0.36	0.96	■									
	Salt	Rep1	0.86	0.70	0.85	0.64	0.48	■								
		Rep2	0.87	0.71	0.85	0.65	0.50	0.97	■							
	Standard	Rep1	0.86	0.69	0.83	0.63	0.47	0.96	0.95	■						
		Rep2	0.87	0.70	0.83	0.64	0.48	0.94	0.96	0.97	■					
		Rep3	0.78	0.63	0.68	0.81	0.71	0.83	0.83	0.82	0.83	■				
	H2O2	Rep1	0.80	0.64	0.72	0.79	0.68	0.86	0.86	0.86	0.86	0.99	■			
		Rep2	0.76	0.59	0.65	0.78	0.70	0.78	0.80	0.77	0.79	0.97	0.96	■		
	Sorbitol	Rep1	0.79	0.64	0.70	0.76	0.66	0.84	0.85	0.82	0.84	0.95	0.95	0.94	■	
		Rep2	0.69	0.54	0.58	0.69	0.62	0.73	0.73	0.71	0.72	0.90	0.88	0.90	0.87	■

Cor between replicates in normal expression
Cor between expression levels (same environment)

Supplementary Table 2

Pearson correlation of fitness effects across replicates, environments, and expression levels. Blue indicates weaker correlations and red stronger correlations. Full black lines indicate correlations between expression levels and double lines indicate correlations between replicates of the same environment. In general the lowest correlations are seen for diamide in high and low expression and salt in low expression. Correlations between replicates are in general strong, except for standard replicate 3. Most correlations are strong, which suggests that in general the fitness effects of mutations should not undergo large changes between environments.

				Deleterious in													
				Low Expression			Normal Expression										
							Diamide		Salt		Standard			H2O2		Sorbitol	
				Standard	Diamide	Salt	Rep1	Rep2	Rep1	Rep2	Rep1	Rep2	Rep3	Rep1	Rep2	Rep1	Rep2
Beneficials in	Low Expression	Standard		63	12.7 (8)	6.35 (4)	14.29 (9)	7.94 (5)	14.29 (9)	6.35 (4)	6.35 (4)	6.35 (4)	9.52 (6)	7.94 (5)	6.35 (4)	4.76 (3)	4.76 (3)
		Diamide		32.99 (65)	197	23.86 (47)	28.43 (56)	23.35 (46)	30.46 (60)	31.47 (62)	16.75 (33)	21.83 (43)	39.59 (78)	45.18 (89)	44.16 (87)	37.56 (74)	28.93 (57)
		Salt		15.91 (14)	27.27 (24)	88	37.5 (33)	27.27 (24)	25 (22)	13.64 (12)	7.95 (7)	6.82 (6)	23.86 (21)	21.59 (19)	23.86 (21)	17.05 (15)	11.36 (10)
	Normal Expression	Diamide	Rep1	19.87 (61)	9.12 (28)	11.4 (35)	307	0 (0)	16.61 (51)	18.24 (56)	6.84 (21)	8.14 (25)	24.43 (75)	26.38 (81)	28.01 (86)	22.8 (70)	14.01 (43)
			Rep2	21.05 (56)	10.9 (29)	12.41 (33)	0.38 (1)	266	19.17 (51)	18.05 (48)	9.02 (24)	9.02 (24)	28.95 (77)	30.83 (82)	30.45 (81)	25.19 (67)	15.79 (42)
		Salt	Rep1	10.94 (7)	12.5 (8)	0 (0)	26.56 (17)	25 (16)	64	6.25 (4)	0 (0)	4.69 (3)	1.56 (1)	3.12 (2)	9.38 (6)	7.81 (5)	1.56 (1)
			Rep2	16.53 (20)	15.7 (19)	4.13 (5)	28.93 (35)	23.14 (28)	6.61 (8)	121	4.13 (5)	0.83 (1)	9.09 (11)	11.57 (14)	11.57 (14)	6.61 (8)	0.83 (1)
		Standard	Rep1	17.33 (39)	18.67 (42)	9.78 (22)	28.89 (65)	27.11 (61)	7.56 (17)	10.22 (23)	225	2.22 (5)	20.44 (46)	20 (45)	20.44 (46)	19.11 (43)	8.89 (20)
			Rep2	21.57 (33)	19.61 (30)	8.5 (13)	33.99 (52)	32.68 (50)	9.15 (14)	5.88 (9)	3.92 (6)	153	24.18 (37)	24.18 (37)	19.61 (30)	12.42 (19)	5.88 (9)
			Rep3	12.4 (16)	13.95 (18)	2.33 (3)	22.48 (29)	19.38 (25)	4.65 (6)	4.65 (6)	2.33 (3)	3.88 (5)	129	0 (0)	10.08 (13)	2.33 (3)	0 (0)
		H2O2	Rep1	11.2 (14)	17.6 (22)	5.6 (7)	24 (30)	17.6 (22)	4.8 (6)	3.2 (4)	2.4 (3)	4 (5)	0.8 (1)	125	4.8 (6)	6.4 (8)	1.6 (2)
			Rep2	12.31 (8)	10.77 (7)	1.54 (1)	21.54 (14)	16.92 (11)	4.62 (3)	1.54 (1)	6.15 (4)	1.54 (1)	4.62 (3)	0 (0)	65	3.08 (2)	1.54 (1)
		Sorbitol	Rep1	15.91 (28)	15.34 (27)	5.11 (9)	27.84 (49)	23.3 (41)	5.68 (10)	2.27 (4)	2.27 (4)	2.84 (5)	5.11 (9)	7.39 (13)	10.23 (18)	176	3.98 (7)
			Rep2	15.1 (37)	16.33 (40)	6.94 (17)	34.29 (84)	29.8 (73)	7.35 (18)	3.67 (9)	4.9 (12)	4.08 (10)	12.24 (30)	16.73 (41)	13.06 (32)	15.1 (37)	245

Percentage of beneficials that have deleterious effect between replicates
Percentage of beneficials that have deleterious effect between levels of expression
Number of beneficials in each environment

Supplementary Table 3

Percentage (and number) of beneficials and their cost across environments. Beneficials in a focal environment (rows) are deleterious in the environment indicated by the column. The diagonal of the matrix indicates the number of beneficials found in each environment/replicate. Yellow shading indicates "spurious costs of adaptation" between pairs

of replicates, which is a proxy for the expected classification error. In general, this error is

low (between 0.38% and 6.61%), except for Replicate 3 in the standard environment and

replicate 2 from Sorbitol, where many beneficial mutations in one replicate are classified as

deleterious in the other. Green highlights the comparisons between levels of expression for

standard, diamide and salt environments. Interestingly, for diamide and salt, the percentage of

beneficials at normal levels of expression that are deleterious at low expression is low, but

there is a larger proportion of beneficials at low expression that is deleterious at high

expression. This pattern in inverted for the standard environment, which is consistent with the

results from Jiang et al 2013.

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