

Evolutionary rescue by aneuploidy in tumors exposed to anti-cancer drugs

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Abstract

Evolutionary rescue occurs when a population, facing a sudden environmental change that would otherwise lead to extinction, adapts through beneficial mutations, allowing it to recover and persist. A prime example of evolutionary rescue is the ability of cancer to survive exposure to treatment. One evolutionary mechanism by which a population of cancer cells can adapt to chemotherapy is aneuploidy. Aneuploid cancer cells can be more fit in an environment altered by anti-cancer drugs, e.g., because aneuploidy disrupts the pathways usually targeted by the drugs. Indeed, aneuploidy is highly prevalent in tumors, and some anti-cancer drugs fight cancer by increasing chromosomal instability. Here, we model the impact of aneuploidy on the fate of a population of cancer cells. We use multi-type branching processes to approximate the probability that a tumor survives drug treatment as a function of the initial tumor size, the rates at which aneuploidy and other beneficial mutations occur, and the growth rates of the drug-sensitive and drug-resistant cells. Additionally, we investigate the effect of the pre-existent aneuploid cells on the probability of evolutionary rescue. Finally, we estimate the tumor's mean recurrence time to revert to its initial size following treatment and evolutionary rescue. We propose that aneuploidy can play an essential role in the relapse of smaller secondary tumors.

Keywords: aneuploidy, evolutionary model, adaptive evolution, cancer, drug resistance, chromosome instability

28 Introduction

Aneuploidy in cancer. Each year, approximately 10 million people die from cancer globally (Kocarnik et al., 2022). Understanding the factors that contribute to the failure of interventions is of great importance. One suggested factor is aneuploidy, in which cells are characterized by an imbalanced karyotype and alterations in the number of chromosomes (Schukken and Foijer, 2018). Aneuploidy is caused by chromosomal instability and mis-segregation of chromosomes during mitosis. Importantly, changes in the number of chromosomes and chromosome arm copies allow cancer cells to survive under stressful conditions such as drug therapy (Ippolito et al., 2021, Lukow et al., 2021, Rutledge et al., 2016). Indeed, cancer cells are often aneuploid, and aneuploidy is associated with poor patient outcomes (Ben-David and Amon, 2020, Smith and Sheltzer, 2018).

Ippolito et al. (2021) induced aneuploidy in cancer cell lines by exposing them to reversine, a small-molecule inhibitor of the mitotic kinase Mps1, and then to anti-cancer drugs such as vemurafenib. Reversine-treated cells had a higher proliferation rate following drug exposure than sensitive cancer cells, due to selection of specific beneficial karyotypes. Similarly, Lukow et al. (2021) induced aneuploidy in cancer cells and observed that such cells have an advantage compared to sensitive cells during drug treatment despite having lower fitness before the onset of treatment. One proposed mechanism through which aneuploidy can confer resistance to anti-cancer drugs is by extending the length of the cell cycle, which prevents the drugs from damaging DNA and microtubules (Replogle et al., 2020). Other mechanisms are the selection for specific karyotypes that lead to reduced drug metabolism (Ippolito et al., 2021) and elevated levels of DNA damage repair due to higher basal levels of DNA damage (Zerbib et al., 2023).

An essential aspect of aneuploidy is that the rate with which cells become aneuploid, that is, the rate of chromosome missegregation, is several orders of magnitude higher than mutation rate (Bakker et al., 2023). Consequently, a cell exposed to stress, such as chemotherapeutic drugs, can acquire aneuploidy faster than a mutation. Furthermore, some proposed anti-cancer drugs elevate the missegregation rate to fight cancer cells (Lee et al., 2016), as an extremely high chromosome missegregation rate is incompatible with cell survival and proliferation.

Evolutionary rescue. Populations adapted to a specific environment are vulnerable to environmental changes, which might cause the population's extinction. Examples of such environmental changes include climate change, invasive species, and the onset of drug therapies. Adaptation is a race against time as the population size decreases in the new environment (Tanaka and Wahl, 2022). *Evolutionary rescue* is the process by which the population acquires an adaptation that increases fitness in the new environment such that extinction is averted. There are three potential ways for a population to survive environmental change (Alexander et al., 2014, Bell, 2017): migration to a new habitat similar to the one before the onset of environmental change (Cobbold and Stana, 2020, Harsch et al., 2014, Zhou, 2022); adaptation by phenotypic plasticity without genetic modification (Carja and Plotkin, 2017, 2019, Gunnarsson et al., 2020, Levien et al., 2021); and adaptation through genetic modifications, e.g., mutation (Gomulkiewicz and Holt, 1995, Orr and Unckless, 2014, Uecker and Hermisson, 2011, 2016, Uecker et al., 2014). Here, we focus on the latter.

There has been extensive theoretical analysis of evolutionary rescue. Orr and Unckless (2008, 2014) thoroughly investigated the simplest case in which there is a specific single mutation or low-frequency variant that is sufficient to rescue the population. Martin et al. (2013) extended these results to consider the effects of a range of rescue genotypes that can vary in both growth rate and variance in offspring number. Uecker and Hermisson (2016) modeled a situation in which *two* mutations at different loci (with recombination between them) are necessary for rescue. Osmond et al. (2020) considered a population that must achieve rescue, potentially via multiple mutations, by adapting on

74 a fitness landscape described by Fisher’s geometric model, and found that for some parameter values
rescue by two mutational steps is more likely than rescue by a single step.

76 Resistance to cancer therapy is a natural application of evolutionary rescue theory (Alexander
et al., 2014). Iwasa et al. (2003) used multi-type branching process theory to approximate the
78 probability that a population under strong selective pressure can survive extinction, focusing on the
case in which the cancer must get two mutations to be rescued, with the single-mutant still dying
80 rapidly. Iwasa et al. (2004) used a similar approach to find simple approximate expressions for the
probability that a single lineage would evolve to survive via a wide range of possible mutational
82 pathways. A very similar set of models describe adaptation to new environments (e.g., a pathogen
evolving to cross a species barrier) and fitness valley crossing (Antia et al., 2003, Weissman et al.,
84 2009). Gunnarsson et al. (2020) analyzed a model where a tumor consisting of two populations of
cancer cells, one drug-resistant and the other drug-sensitive, can evade extinction by cells switching
86 between the two phenotypes through epigenetic mutations. They found that even when drug-resistant
cells are barely viable, the epimutations guarantee evolutionary rescue.

88 Here, we study evolutionary rescue after a sudden environmental change caused by initiating
anti-cancer drug treatment. Essentially, this consists of combining known results from the evolutionary
90 rescue literature, focusing on the quantities and parameter values that are relevant for cancer. Because
these results are scattered across multiple papers, and because they all follow from simple branching
92 process approximations, we re-derive all results here for our model. While our focus is on the
application of evolutionary rescue theory to evolution of drug resistance in cancer, our model is a
94 general one, and in the general evolutionary rescue context, this work can be seen as a characterization
of the circumstances in which two-step processes contribute to rescue even when single-step rescue
96 mutations are available, similar to part of Osmond et al. (2020) but focused on a different fitness
landscape.

98 We consider a range of effects of aneuploidy, from tolerance to (partial) resistance to the drug
(Brauner et al., 2016); note that we use tolerant to refer to aneuploids which have negative growth
100 rates, which is different from other references in the literature such as Berman and Krysan (2020). We
estimate the effect of aneuploidy on the tumor’s evolutionary rescue probability. When aneuploidy
102 provides drug resistance, it can directly rescue the tumor. However, when aneuploidy provides
tolerance to the drug, it may act as an evolutionary “stepping stone” or “springboard” (Martin et al.,
104 2013, Osmond et al., 2020, Yona et al., 2015), delaying extinction, and thereby allowing the tumor
more time to acquire a resistance mutation on top of the aneuploid background. As mentioned above,
106 evidence suggests that aneuploidy may be a common strategy for tumor adaptation to drug therapy.
Still, it is unknown how often aneuploidy provides tolerance and acts as a stepping stone. We also
108 estimate the mean time until a tumor cell population reaches its pre-treatment size following drug
therapy. Given that aneuploidy is present in many tumors before the onset of therapy (Ben-David and
110 Amon, 2020, Lukow et al., 2021), we also consider the effect of pre-treatment standing genetic variation
on the evolutionary dynamics. Additionally, we are interested in the timescale of evolutionary rescue
112 and the impact that aneuploidy has on the time necessary for the tumor to overcome drug therapy.

Methods

114 **Evolutionary model.** We follow the number of cancer cells with one of three different genotypes at
time t : sensitive, s_t ; tolerant/resistant aneuploid, a_t ; and resistant mutant, m_t . These cells divide and
116 die with rates λ_k and μ_k (for $k = s, a, m$). The division and death rate difference is $\Delta_k = \lambda_k - \mu_k$. We
assume the population of cells is under a strong stress, such as drug therapy, and therefore $\Delta_s < 0$,
118 whereas the mutant is resistant to the stress, $\Delta_m > 0$. We consider a range of possible values for Δ_a ,
finding three distinct scenarios: in the first, aneuploid cells are partially resistant, $\Delta_m > \Delta_a > 0$; in

120 the second, aneuploid cells are tolerant, $0 > \Delta_a > \Delta_s$ (see Brauner et al., 2016, for the distinction
 122 between susceptible, resistant, and tolerant); in the third, aneuploid cells are non-growing, stationary,
 or growing or dying only very slowly, that is, either slightly tolerant or slightly resistant, such that
 $\Delta_a \approx 0$, in a sense that we will make precise below.

124 We assume that both chromosomal missegregation and mutations occur during the process
 of mitosis. Sensitive cells may divide and then missegregate to become aneuploids at rate $u\lambda_s$.
 126 Both aneuploid and sensitive cells may divide and mutate to become mutants at rates $v\lambda_a$ and $v\lambda_s$,
 respectively. To model standing genetic variation, we assume that before the onset of therapy, sensitive
 128 cells become aneuploid with rate $\tilde{u}\lambda_s$ (which may differ from $u\lambda_s$) and that aneuploidy confers a fitness
 cost c in the drug-free environment, that is, we assume that aneuploid cells have an increased death rate
 130 compared to sensitive cells in a drug-free environment. We assume that c is not too small (Table 1),
 so that standing variation is generated by a balance between the generation of anuploids and selection
 132 against them, without the effect of genetic drift.

See Figure 1 for a schematic representation of the model and Figure 2 for sample trajectories of
 134 the different genotypes.

Stochastic simulations. Simulations are performed using the *Gillespie stochastic simulation algo-*
 136 *rithm* (Gillespie, 1976, 1977) implemented in Python (Van Rossum and Others, 2007). The simulation
 monitors the number of cells of each type: sensitive, aneuploid, and mutant. Initially, the population
 138 starts with only sensitive cells, $s_0 = N$, and the other genotypes are initially absent.

The cell population at time t is represented by the triplet (s_t, a_t, m_t) . The following describes the
 140 events that may occur (right column), the rates at which they occur (middle column), and the effect
 these events have on the population (left column, see Figure 1):

| | | | |
|-----|----------------|-----------------------------|--|
| | $(+1, 0, 0) :$ | $\lambda_s s_t (1 - u - v)$ | (birth of sensitive cell) , |
| | $(-1, 0, 0) :$ | $\mu_s s_t$ | (death of sensitive cell) , |
| | $(0, +1, 0) :$ | $u\lambda_s s_t$ | (sensitive cell divides and becomes aneuploid) , |
| | $(0, 0, +1) :$ | $v\lambda_s s_t$ | (sensitive cell divides and becomes mutant) , |
| 142 | $(0, +1, 0) :$ | $\lambda_a a_t (1 - v)$ | (birth of aneuploid cell) , |
| | $(0, -1, 0) :$ | $\mu_a a_t$ | (death of aneuploid cell) , |
| | $(0, 0, +1) :$ | $v\lambda_a a_t$ | (aneuploid cell divides and becomes mutant) , |
| | $(0, 0, +1) :$ | $\lambda_m m_t$ | (birth of mutant cell) , |
| | $(0, 0, -1) :$ | $\mu_m m_t$ | (death of mutant cell) . |

For the remainder of this paper, we assume that the division rates of sensitive and aneuploid cells
 144 can be written as $\lambda_s s_t (1 - u - v) \approx \lambda_s s_t$ and $\lambda_a a_t (1 - v) \approx \lambda_a a_t$ because $u, v \ll 1$ (Table 1). Each
 iteration of the simulation loop starts by computing the rates ν_k of each event k . We then draw the
 146 time until the next event, Δt , from an exponential distribution whose rate parameter is the sum of the
 rates of all events, such that $\Delta t \sim \text{Exp}(\sum_j \nu_j)$. Then, we randomly determine which event occurred,
 148 where the probability for event k is $p_k = \nu_k / \sum_j \nu_j$. Finally, we update the number of cells of each
 genotype according to the event that occurred and update the time from t to $t + \Delta t$. We repeat these
 150 iterations until either the population becomes extinct (the number of cells of all genotypes is zero) or
 the number of mutant cells is high enough so that their extinction probability is $< 0.1\%$, that is, until

$$152 \quad m_t > \left\lceil \frac{3 \log 10}{\log (\lambda_m / \mu_m)} \right\rceil + 1,$$

which we obtain by solving $1 - (1 - p_m)^{m_t} = 0.999$ for m_t with $p_m = \Delta_m / \lambda_m$ as the probability that a
 154 single mutant escapes stochastic extinction (Appendix A).

When simulations are slow (e.g., due to large population size) with runtimes in the order of
 156 days, we use τ -leaping (Gillespie, 2001), where we assume that the change in the number of cells of
 genotype k in a fixed time interval Δt is Poisson distributed with mean $\nu_k \Delta t$. If the number of cells of
 158 genotype k becomes negative, we change it to zero.

Parameterization. We parametrize most of our simulations by considering melanoma cells and rely
 160 on Rew and Wilson (2000) and Bozic et al. (2013) for the division and death rates, respectively. Rew
 and Wilson (2000) report *in vivo* measurements of the potential doubling times (the waiting time for
 162 the number of cells in the tumor to double, disregarding cell death) for a large set of cancer types. The
 division rate is obtained as $\lambda = \log 2 / T \approx 0.1$ per day. We take this to be the division rate for sensitive
 164 and assume that mutant cells, which are resistant to therapy, have the same division rate. Indeed,
 doubling times for tumors after relapse is lower than that of primary tumors for a variety of tissues (??)
 166 and metastatic melanoma has been shown to grow faster than primary melanoma (Carlson, 2003).

Bozic et al. (2013) report the growth rate Δ_s for sensitive melanoma cancer cells, from patient
 168 data, from which they deduce the death rate $0.11 \leq \mu_s \leq 0.17$. We use $\mu_s = 0.14$ per day. Additionally,
 they observed the growth rate of cancer cells before treatment to be 0.01, which we use as the growth
 170 rate of mutant cells, which are resistant to the drug. Thus, we use $\mu_m = 0.1 - 0.01 = 0.09$ per day as
 the death rate for mutant cells.

The aneuploid death rate μ_a is set to the mutant death rate, $\mu_m = 0.09$ per day, assuming
 172 aneuploidy increases resistance to the drug, such as cisplatin, by antagonizing cell division (Replogle
 et al., 2020). For the aneuploid growth rate to be intermediate between those of sensitive and mutant
 174 cells, $\Delta_s \ll \Delta_a \ll \Delta_m$, we set the aneuploid division rate to be $0.06 \leq \lambda_a \leq 0.1$. In most of our
 simulations, we use $\lambda_a = 0.0899$ per day, so that aneuploid cells are tolerant and aneuploidy can only
 176 act as an evolutionary “stepping stone” for the generation of the resistant mutant that rescues the tumor
 178 (note that this mutant will occur on the background of an aneuploid genotype).

In some of the analysis, we consider breast cancer. We assume that the division and death rates of
 180 the aneuploid breast cancer cells in the presence of cisplatin is the same as those of the sensitive cells
 in the absence of the drug. The growth rate of breast cancer cells in the absence of drug is 0.0085 per
 182 day (Spratt et al., 1996). The doubling time of breast cancer cells in the absence of cellular death is 8.2
 days (Rew and Wilson, 2000). Thus, the division rate of aneuploid cells is $\lambda_a = \log(2)/8.2 = 0.0845$
 184 per day, and their death rate is $\mu_a = 0.076$ per day. For the division and death rates of sensitive cells,
 we turn to results described in Salehi et al. (2021). We select TNBC-SA535 PDX clone H, which has
 186 a relative fitness of ≈ 1.011 . Thus, the selection coefficient is the ratio of the aneuploid and sensitive
 Wrightian fitness values minus 1 (Chevin, 2011). The Malthusian fitness is the log of the Wrightian
 188 fitness (Wu et al., 2013). Thus, $\Delta_s = \log 0.9975 - 0.0025$. We assume cisplatin affects cancer cells by
 increasing their death rate but does not affect their division rate, hence $\lambda_s = 0.08$ and $\mu_s = 0.0825$
 190 per day. A similar analysis for TNBC-SA609 clone A and TNBC-SA1035 clone H from Salehi et al.
 (2021) gives $\lambda_s = 0.08$, $\mu_s = 0.12$ and $\lambda_s = 0.08$, $\mu = 0.1$, respectively.

The missegregation rate in cancer cells is estimated to be between $2.5 \times 10^{-4} - 10^{-2}$ per chro-
 192 mosome per cell division (Shi and King, 2005, Thompson and Compton, 2008). Ippolito et al. (2021)
 194 observed that trisomy in Chr 2 and Chr 6 are most likely to confer increased resistance against the
 anti-cancer drug vemurafenib for A375 cells. We assume each of these trisomies is formed at the most
 196 likely rate, and as a result, we use $\tilde{u} = 10^{-3}$ per cell division as the chromosome missegregation rate in
 the drug-free environment. Some drugs are known to increase chromosome instability (Mason et al.,
 198 2017, Wang et al., 2019). Specifically, Lee et al. (2016) estimated the effect of different anti-cancer

drugs on the missegregation rate and found a 3-50-fold increase. We thus assume an anti-cancer drug
 200 that causes a 10-fold increase in the chromosome missegregation rate, which gives us $u = 10^{-2}$ per
 cell division. We assume the mutation rate is 10^{-7} per gene per cell division (Loeb, 2001), and since
 202 we assume that a single target gene confers resistance to the drug, we use $v = 10^{-7}$ per cell division.

To estimate fitness cost of aneuploidy, c , we note that Lukow et al. (2021) mixed sensitive and
 204 aneuploid A375 melanoma cells at 1 : 1 ratio, cultured them in a drug-free environment, and observed
 the ratio evolve as a function of time with the aneuploid cells declining to 15% after 24 days. Thus,
 206 our estimate for the fitness cost is $c = |\log(0.15/(1 - 0.15)) / 24| \approx 0.07$ per day (Chevin, 2011). We
 estimate the fraction of aneuploid cancer cells in the pre-treatment environment using the formula
 208 $f = \tilde{u}\lambda_s/c$, which produces an estimate of $f = 10^{-3} \times 10^{-1}/0.07$, that is, 0.14% of pre-treatment
 cancer cells have the beneficial aneuploidy of interest.

210 We note that when we refer to drug-sensitive cells, we include those cells that have any aneuploidy
 other than trisomy in Chr 2 and 6, as those are the aneuploid cells that are hypothesized to have
 212 higher fitness in the environment altered by drugs such as vemurafenib. Additionally, in our model,
 mutations only confer resistance, however, most mutations are deleterious. We consider the fitness of
 214 the sensitive, aneuploid or mutant cells to be the average of each population. As a result, mutations
 that are deleterious are taken into consideration through the mean fitness of each population.

216 All the parameters discussed above are shown in Table 1.

Density-dependent growth. In most of our analysis, we assume that cells from the initial population
 218 divide and die independently of each other. However, these cells will compete for resources. We
 assume this competition can be ignored because the drug will cause the cell density to rapidly drop
 220 below the carrying capacity where competition is important. To test this assumption, we simulate a
 logistic growth model, with division and death rates given by

$$\begin{aligned} \lambda'_s &= \lambda_s, \\ \mu'_s &= \mu_s + \lambda_s \frac{s + a + m}{K}, \\ \lambda'_a &= \lambda_a, \\ 222 \quad \mu'_a &= \mu_a + \lambda_a \frac{s + a + m}{K}, \\ \lambda'_m &= \lambda_m, \\ \mu'_m &= \mu_m + \lambda_m \frac{s + a + m}{K}, \end{aligned}$$

where K is the tumor carrying capacity. The effective carrying capacity in this model is $K_e =$
 224 $K\Delta_a/\lambda_a \approx 10^6$ for $K = 10^8$, $\lambda_a = 0.0901$, $\mu_a = 0.09$, where we define the effective carrying capacity
 to be the population size at which the aneuploid division rate is equal to the aneuploid death rate.

226 **Code and data availability.** All source code is available online at <https://github.com/yoavram-lab/EvolutionaryRescue>.

228 Results

Evolutionary rescue probability

230 In our model, *evolutionary rescue* occurs when drug-resistant cells appear and establish (avoid random
 extinction) in the population ($m_t \gg 1$) before the population becomes extinct ($s_t = a_t = m_t = 0$).
 232 Aneuploidy may contribute to evolutionary rescue by either preventing (when $\Delta_a > 0$) or delaying

(when $0 > \Delta_a > \Delta_s$) the extinction of the population before mutant cells appear and establish. We
 234 assume independence between clonal lineages starting from an initial population of N sensitive cells
 (we check the effect of density-dependent growth on our results below) and therefore, we use multi-
 236 type branching processes to model the dynamics of the cancer cell population. Multi-type branching
 process models the growth and evolution of populations with distinct types, capturing dynamics like
 238 mutation and selection. In evolutionary rescue, it predicts the probability of population survival by
 tracking adaptive mutations that emerge and spread under environmental stress. Define p_s as the
 240 probability that a lineage starting from a single drug-sensitive cell avoids extinction by acquiring drug
 resistance. Thus, $N^* = 1/p_s$ is the threshold tumor size above which evolutionary rescue is very likely
 242 (Iwasa et al., 2003), and the rescue probability is given by

$$p_{\text{rescue}} = 1 - (1 - p_s)^N \approx 1 - e^{-Np_s} = 1 - e^{-N/N^*}, \quad (1)$$

244 where the approximation $(1 - p_s) \approx e^{-p_s}$ assumes that p_s (but not necessarily Np_s) is small. Indeed,
 when $N < 1/p_s$, then the probability for evolutionary rescue is $p_{\text{rescue}} \approx Np_s$, and when $N > 1/p_s$, it
 246 is $p_{\text{rescue}} \approx 1$, justifying the definition of N^* as the threshold tumor size for evolutionary rescue.

We use multi-type branching-process theory to find approximate expressions eqs. (A4), (A7)
 248 and (A11) for p_s in three distinct scenarios (Appendix A). Substituting these into $N^* = 1/p_s$, we
 find approximations for the threshold tumor size, N^* . In these approximations, an important quantity
 250 is $T^* = \sqrt{\lambda_m/4v\lambda_a^2\Delta_m}$, which is the critical time an aneuploid lineage needs to survive to produce
 a resistant mutant that avoids random extinction. First, if aneuploidy is very rare ($u\lambda_a T^* < 1$), or
 252 if aneuploidy is rare ($u\lambda_a < -\Delta_a$) and very sensitive to the drug ($\Delta_a T^* < -1$), then it is likely
 that evolutionary rescue will occur through a direct resistance mutation in a sensitive cell without
 254 aneuploidy playing a role in the adaptive dynamics, such that

$$N_m^* \approx \frac{|\Delta_s|}{v\lambda_s} \frac{\lambda_m}{\Delta_m}, \quad (2)$$

256 which is similar to a classical result by Orr and Unckless (2008). Here, $|\Delta_s|/(v\lambda_s)$ is the ratio of the
 rate at which sensitive cells decrease in number and the rate at which they are mutating. Notably, the
 258 aneuploidy parameters (u, λ_a, μ_a) do not affect N_m^* .

Otherwise, aneuploidy is frequent enough ($u\lambda_a > \max(-\Delta_a, 1/T^*)$) to affect the evolution of
 260 drug resistance. The threshold tumor size can be approximated by one of the following scenarios,
 depending on $\Delta_a T^*$, which represents the change in the aneuploid log-population size during the
 262 critical time,

$$N_a^* \approx \frac{|\Delta_s|}{u\lambda_s} \cdot \begin{cases} \frac{|\Delta_a|}{v\lambda_a} \frac{\lambda_m}{\Delta_m}, & \Delta_a T^* \ll -1 \text{ (tolerant aneuploids),} \\ 2\lambda_a T^*, & -1 \ll \Delta_a T^* \ll 1 \text{ (stationary aneuploids),} \\ \frac{\lambda_a}{\Delta_a}, & \Delta_a T^* \gg 1 \text{ (resistant aneuploids).} \end{cases} \quad (3)$$

264 This equation is equivalent to eq. A3 of Iwasa et al. (2004) and to eq. 8 of Osmond et al. (2020) with
 the distribution of fitness effects set to a delta function; our “tolerant”, “stationary”, and “resistant”
 266 scenarios correspond to Osmond et al. (2020)’s “sufficiently subcritical”, “sufficiently critical”, and
 “sufficiently supercritical”, respectively. These approximations are accurate when compared to results
 268 of stochastic evolutionary simulations (Figures 3 and 4). In the first scenario, the treatment effectively
 kills aneuploid cells but not as quickly as it kills sensitive cells. In the second scenario, aneuploid
 270 cells are sufficiently resistant, and the expected size of each aneuploid lineage is roughly 1. In both
 of these scenarios, aneuploidy increases the probability of rescue by slowing or halting the decrease
 272 in the tumor population size, allowing more opportunities to produce resistant mutants. In the third
 scenario, aneuploid cells are sufficiently resistant for the population to re-grow the tumor without
 274 additional resistance mutations. Notably, in this scenario the mutant parameters (v, λ_m , and Δ_m) do

not affect N_a^* beyond their effect on T^* . In all scenarios, N_a^* is proportional to $1/u$ such that increasing
 276 the missegregation rate u will decrease the threshold tumor size (Figure 4B). Furthermore, increasing
 the aneuploid growth rate Δ_a (which appears both in the terms and in the conditions), also reduces
 278 the threshold tumor size, with a sharp decrease around $\Delta_a = 0$, but the effect is minor when $|\Delta_a|$ is
 small compared to T^* as this would result in the second scenario where $dN_a^*/d\Delta_a = 0$ (Figure 4A).
 280 The tumor threshold size decreases with the mutation rate in the first and second scenarios: N_a^* is
 proportional to $1/v$ in the first scenario (tolerant aneuploids) and to $\sqrt{1/v}$ in the second scenario
 282 (stationary aneuploids). Furthermore, the growth rate $\Delta_a < 0$ that allows tolerant aneuploids to rescue
 the tumor is between $-u\lambda_a$ and $-1/T^*$, which is proportional to $-\sqrt{v}$. Thus, increasing the mutation
 284 rate v will decrease the tumor threshold size N_a^* , making evolutionary rescue more likely, but only
 until T^* decreases to a point where $\Delta_a = 1/T^*$.

286 Using eqs. (2) and (3), we can find the ratio of threshold tumor size for rescue via aneuploidy (u
 is high) or via direct mutation (u is low),

$$288 \quad \frac{N_a^*}{N_m^*} \approx \begin{cases} \frac{|\Delta_a|}{u\lambda_a}, & \Delta_a T^* \ll -1, \\ \frac{1}{u} \left(v \frac{\Delta_m}{\lambda_m} \right)^{1/2}, & -1 \ll \Delta_a T^* \ll 1, \\ v \frac{\Delta_m}{\lambda_m} \left(u \frac{\Delta_a}{\lambda_a} \right)^{-1}, & \Delta_a T^* \gg 1. \end{cases} \quad (4)$$

As expected, this ratio increases with the mutation rate v and decreases with the aneuploidy rate u . In
 290 the first scenario, $|\Delta_a|/u\lambda_a$ is the ratio of the expected time for an aneuploid lineage to appear, $1/u\lambda_a$,
 and the expected time until that lineage disappears, $1/|\Delta_a|$. In the third scenario, $\left(v \frac{\Delta_m}{\lambda_m} \right) / \left(u \frac{\Delta_a}{\lambda_a} \right)$ is
 292 the ratio of the rates of appearance of resistant mutants that avoid extinction and partially resistant
 aneuploids that avoid extinction. In the second scenario, $\frac{1}{u} \left(v \frac{\Delta_m}{\lambda_m} \right)^{1/2} = \sqrt{\frac{\Delta_a}{u\lambda_a} v \frac{\Delta_m}{\lambda_m} \left(u \frac{\Delta_a}{\lambda_a} \right)^{-1}}$, which is
 294 the geometric mean of the first and third scenarios.

Interestingly, increasing both the aneuploid division rate, λ_a , and the aneuploid death rate, μ_a ,
 296 such that the growth rate Δ_a remains constant, leads to a decrease in T^* , pushing the system to
 the second scenario (increasing λ_a causes a decrease in T^* because it increases the mutation rate
 298 and a lineage does not have to survive as long in order to generate a successful mutant). In this
 scenario, increasing the division rate λ_a should also increase the mutation rate $v\lambda_a$ in aneuploid cells,
 300 as mutations mostly occur during division, so overall, the threshold tumor size N_a^* is unaffected by
 the division rate λ_a (i.e., $d\lambda_a T^*/d\lambda_a = 0$). Thus, if aneuploid cells rapidly die due to the drug but
 302 compensate by rapidly dividing, increasing the division rate will *not* facilitate adaptation. This is
 consistent with experimental findings where aneuploidy confers resistance by decreasing the division
 304 rate which in turn decreases the death rate as certain drugs affect cancer cells during division (Replogle
 et al., 2020).

306 We can categorize tumors by their size: small tumors with size $N < N_a^*$ that are unlikely to survive
 treatment, intermediate tumors with size $N_a^* < N < N_m^*$ that rely on aneuploidy for evolutionary
 308 rescue, and large tumors with size $N > N_m^*$ that could overcome the effect of drug treatment without
 aneuploidy. For the parameter values in Table 1 with $\lambda_a = 0.0899$, $\mu_s = 0.14$, $u = 10^{-2}$, $v = 10^{-7}$,
 310 we are in the tolerant aneuploid scenario, and substituting in eqs. (2) and (3), we have $N_a^* \approx 4 \times 10^6$
 and $N_m^* \approx 4 \times 10^7$. Hence, we obtain the ratio $N_a^*/N_m^* \approx 0.11$ (eq. (4)), that is, aneuploidy reduces
 312 the threshold tumor size by approximately 89%. Interestingly, the threshold between small and
 intermediate tumors, N_a^* , is similar to the tumor detection threshold of 4.19×10^6 cells for a wide
 314 variety of tumors (Avanzini and Antal, 2019). We note that vemurafenib-treated melanomas (i.e.
 melanomas with sizes above the detection threshold) have a probability $> 50\%$ to relapse (Handa
 316 et al., 2022, Piejko et al., 2023).

Aneuploidy may lead to an increased mutation rate in cancer cells (Garribba et al., 2023, Janssen et al., 2011, Passerini et al., 2016). Thus, we extended our model to account for this in Appendix H. We find that increasing the mutation rate in aneuploid cells by one order of magnitude leads to a decrease in the threshold tumor size of approximately one order of magnitude. Also, it transitions the system from the first scenario (tolerant aneuploids) to the second scenario (stationary aneuploids) without changing the aneuploid growth rate, Δ_a .

In our analysis, we used branching processes, which assume that growth (division and death) is density-independent. However, growth may be limited by resources (oxygen, nutrients, etc.) and therefore depend on cell density. Therefore, we performed stochastic simulations of a logistic growth model with a carrying capacity. We find that our density-independent approximations agree with the results of simulations with density-dependent growth for biologically relevant parameter values (Figure S1).

Standing vs. *de novo* genetic variation. In the above, we assumed that at the onset of drug treatment, the initial tumor consisted entirely of drug-sensitive cells. However, aneuploidy is likely produced even before the onset of treatment at some rate \tilde{u} , which may be lower in the absence of drugs, $\tilde{u} < u$ (Mason et al., 2017, Wang et al., 2019). Moreover, aneuploidy likely confers a fitness cost c in the absence of drugs (Giam and Rancati, 2015, Replogle et al., 2020). Hence, if the number of cells in the tumor N is large (as expected if the tumor is treated with a drug), there may already be a fraction $f \approx \tilde{u}\lambda_s/c$ of aneuploid cells in the population (here we assume that the drug affects the sensitive death rate but not the division rate and therefore we use λ_s for the sensitive division rate in the drug-free environment).

Therefore, the threshold tumor size for rescue by standing generation variation, \tilde{N}_a^* , is similar to the threshold for rescue by *de novo* variation, N_a^* , except that the sensitive growth rate $|\Delta_s|$ is replaced by the cost of aneuploidy c , such that

$$\frac{\tilde{N}_a^*}{N_a^*} = \frac{u}{\tilde{u}} \frac{c}{|\Delta_s|}. \quad (5)$$

This result has been previously reported by Orr and Unckless (2008) for the one-step evolutionary rescue and by Martin et al. (2013) for two-step evolutionary rescue. Comparing this approximation of \tilde{N}_a^*/N_a^* to results of stochastic simulations, we find that the approximations are accurate (Figure 5). Standing genetic variation will drive evolutionary rescue if sensitive cells die rapidly (growth rate Δ_s is very negative) due to a strong effect of the drug on sensitive cells or if the cost of aneuploidy in the drug-free environment, c , is small. In contrast, *de novo* aneuploid cells will have a greater contribution to rescue if the cost of aneuploidy, c , is large, the effect of the drug on sensitive cells is weak (Δ_s is close to zero), or if the drug induces the appearance of aneuploid cells ($u > \tilde{u}$). For example, with $\lambda_s = 0.1$, $\mu_s = 0.14$, $u = 10^{-2}$, $\tilde{u} = 10^{-3}$, and $c = 0.07$, the ratio of the threshold tumor sizes for standing vs. *de novo* variation is $\tilde{N}_a^*/N_a^* \approx 17.5$, which means that *de novo* genetic variation is the main driver of evolutionary rescue.

Using eqs. (2), (3) and (5), we can find the ratio of threshold tumor size for rescue via standing genetic variation to the threshold for rescue via direct mutation,

$$\frac{\tilde{N}_a^*}{N_m^*} = \frac{\tilde{N}_a^*}{N_a^*} \frac{N_a^*}{N_m^*} \approx \frac{c}{|\Delta_s|} \begin{cases} \frac{|\Delta_a|}{\tilde{u}\lambda_a}, & \Delta_a T^* \ll -1, \\ \frac{1}{\tilde{u}} \left(v \frac{\Delta_m}{\lambda_m} \right)^{1/2}, & -1 \ll \Delta_a T^* \ll 1, \\ v \frac{\Delta_m}{\lambda_m} \left(\tilde{u} \frac{\Delta_a}{\lambda_a} \right)^{-1}, & \Delta_a T^* \gg 1. \end{cases} \quad (6)$$

Evolutionary rescue through direct mutation is more likely if the cost of aneuploidy, c , is very large or the effect of the drug Δ_s is small. In contrast, standing genetic variation will drive adaptation if

the pre-treatment chromosome missegregation rate, \tilde{u} , is very large. The ratio does not depend on the rate of chromosome missegregation induced by the drug, u . However, if the aneuploid growth rate, Δ_a , increases, evolutionary rescue is driven by standing genetic variation. For the parameter values of $\lambda_s = 0.1$, $\lambda_a = 0.0899$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $\tilde{u} = 10^{-3}$, and $v = 10^{-7}$, we are in the first scenario (tolerant aneuploids) and obtain the ratio $\tilde{N}_a^*/N_m^* \approx 1.94$, which means that standing genetic variation does not drive evolution of drug resistance when compared to direct mutation. We note that for larger values of the pre-treatment chromosome missegregation rate, \tilde{u} , which are consistent with empirical studies (Table 1), standing genetic variation can drive adaptation when compared to direct mutation.

Recurrence time due to evolutionary rescue

When evolutionary rescue occurs, the time until the tumor recurs may still be very long. We therefore explored the time until the tumor recurs, that is, the time until the tumor reaches its original size, N . When the expected number of resistant lineages that avoid extinction is small, the expected recurrence time can be estimated by adding two terms: the *mean evolutionary rescue time*, which is the waiting time for the appearance of a resistant lineage that avoids extinction (conditioned on such an event occurring in the first place), and the *mean proliferation time*, which is the expected time for that lineage to grow to N cells. However, when the expected number of resistant lineages is large, the mean recurrence time cannot be separated into the mean evolutionary rescue time and mean proliferation time because multiple mutant lineages contribute towards the mutant population size reaching the initial tumor size. In this case the dynamics of the number of mutant cells is deterministic and can therefore be modeled by a system of ordinary differential equations (ODE), which describe how the number of mutant cells changes over time by its time derivative (eq. D2). Of particular interest is the distribution of the evolutionary rescue time and recurrence time with tolerant aneuploid cells ($\Delta_a T^* \ll 1$), for which we focus on the parameter values $\lambda_s = 0.1$, $\lambda_a = 0.0899$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $u = 10^{-2}$, and $v = 10^{-7}$.

Evolutionary rescue time. We have derived approximations for τ_m , the mean evolutionary rescue time without aneuploidy ($u = 0$), and τ_a , the mean rescue time with aneuploidy ($u > 0$), both conditioned on evolutionary rescue occurring (Appendix C). These approximations agree with simulation results for small, intermediate, and large tumor sizes (Figures S2 and S6). The mean rescue time with aneuploidy for small and large tumors follows

$$\tau_a \approx \begin{cases} -\frac{1}{\Delta_s} - \frac{1}{\Delta_a}, & N \ll N_a^*, \\ \frac{1}{v\lambda_s N} \frac{\lambda_m}{\Delta_m}, & N \gg N_m^*. \end{cases} \quad (7)$$

For small tumors ($N \ll N_a^*$), the mean rescue time is the two-step equivalent of the one-step result from Orr and Unckless (2014, expectation of eq. 18). The mean rescue time (conditioned on rescue occurring) is a decreasing function of the sensitive and aneuploid growth rates and independent of the other model parameters, including tumor size (blue line in Figure S6). This is because if the population rapidly declines but is then rescued, then the resistance mutation must have appeared early; if the population slowly declines, then mutations can appear later and the mean time will be longer. In our focus parameter regime, we have $\Delta_s = -0.04$ and $\Delta_a = -10^{-4}$, such that the mean rescue time is mainly determined by the aneuploid growth rate, $\tau_a \approx 10^4$ days.

For large tumors ($N \gg N_m^*$), the dynamics are equivalent to a scenario where rescue mutations appear at a constant rate, and the mean rescue time (eq. (7)) is independent of the aneuploid parameters (u , λ_a , and Δ_a). Increasing the per division mutation rate, v , leads to the faster appearance of a rescue mutations and hence reduced mean rescue time. Finally, increasing the tumor size leads to shorter mean rescue time, as more sensitive cells can mutate to become resistant.

402 Given that a fraction $f \approx 0.14\%$ of the initial cancer cell population is expected to have beneficial
 403 aneuploidy even before the onset of drug treatment, we want to know whether the mean evolutionary
 404 rescue time is affected by the standing genetic variation. We calculated the mean evolutionary
 405 rescue time with standing genetic variation, $\tilde{\tau}_a$ (eq. (C10)), and compared our result with simulations
 406 (Figure S9). We note that standing genetic variation does not significantly affect the mean evolutionary
 rescue time.

408 We calculate the probability that a rescue mutation has been generated by time t in Appendix E.
 This allows us to examine whether aneuploidy promotes or delays evolutionary rescue. We find
 410 that aneuploidy promotes evolutionary rescue after $1/\Delta_s \approx 100$ days, at a time when no more
 rescue mutations are generated through mutations in sensitive cells (Figure 6A). Thus, aneuploidy
 412 increases the *window of opportunity* for evolutionary rescue. This can have a counter-intuitive
 outcome: conditioned on the rescue of the tumor, tumors rescued by aneuploid cells may acquire
 414 rescue mutations later than those rescued by sensitive cells.

Recurrence time. We next approximated the mean time for the population of mutant cancer cells
 416 to reach the initial, pre-treatment population size N , which we denote the recurrence time τ_a^r (Ap-
 pendix D),

$$418 \quad \tau_a^r \approx \begin{cases} -\frac{1}{\Delta_s} - \frac{1}{\Delta_a} + \frac{\log p_m N}{\Delta_m}, & N \ll N_a^*, \\ \frac{1}{\Delta_m} \log \frac{\Delta_m - \Delta_s}{v \lambda_s}, & N \gg N_m^*, \end{cases} \quad (8)$$

where p_m is the probability that a lineage starting from a single mutant cell escapes stochastic
 420 extinction. Figures 7 and S7 show the agreement between our approximations and simulation results.
 For small tumors ($N \ll N_a^*$), the mean recurrence time can be approximated as the sum of the mean
 422 time for the first rescue mutation to appear (τ_a) and the additional mean time for its lineage to reach
 size N . This additional time is the equivalent of Orr and Unckless (2014)'s " t_{return} " (their eq. 23).
 424 It grows logarithmically with tumor size N and may be the same order of magnitude as the mean
 evolutionary rescue time. Increasing the mutant growth rate, Δ_m , decreases the recurrence time, while
 426 increasing the sensitive and aneuploid growth rates, Δ_s and Δ_a , respectively, increases the recurrence
 time.

428 For large tumors ($N \gg N_m^*$), the dynamics of the number of mutant cells is deterministic, and the
 mean recurrence time becomes independent of the initial tumor size N . Increasing either the mutant
 430 growth rate, Δ_m , or the mutation rate, v , decreases the time for the tumor to rebound to its initial size.
 Drugs that significantly increase the death rate of sensitive cells, μ_s , but do not affect their division
 432 rate, λ_s , delay cancer recurrence. Additionally, decreasing the sensitive division rate will also the
 cancer recurrence time. Consequently, patients treated with such drugs may require a longer period
 434 of monitoring to guarantee the effectiveness of the treatment. In addition, drugs that significantly
 increase the division rate of sensitive cells, λ_s , but do not affect their death rate, μ_s , decrease cancer
 436 recurrence times (conditioned on evolutionary rescue).

We note that, for small and large tumors, when $N \ll N_a^*$ or $N \gg N_m^*$, the asymptotic expressions
 438 for the mean recurrence time are independent of the chromosome missegregation rate u , and therefore,
 the rate at which the drug induces aneuploidy has no effect on the time for the tumor to rebound to its
 440 initial size N .

Appendix F gives us the probability that a mutant cancer cell population has not reached size N
 442 by time t . Figure 6B shows agreement between our approximations and simulation results for various
 values of N . Additionally, we derive the distribution of the recurrence time for a small tumor with
 444 $N = 10^6$ cells, noting that the distribution is wide and right-skewed (Figure S4). It is highly unlikely
 to observe the recurrence of cancer at times smaller than $\frac{1}{\Delta_m} \log \frac{\Delta_m - \Delta_s}{v \lambda_s} \approx 1500$ days for the parameter

446 values in Table 1 with $\lambda_a = 0.0899$, $\mu_s = 0.14$, and $\nu = 10^{-7}$ and independent of initial tumor size N (Figure 6B).

448 The detection time τ_a^M is defined as the time for the tumor size to reach detection threshold M . We derive the mean detection time for $M = 10^7$ in Appendix D. We find that for small and
450 intermediate-sized tumors the mean detection time is approximately equal to the mean recurrence time (i.e., $\tau_a^r \approx \tau_a^M$ for $N < N_m^*$). However, for large tumors, the mean detection time τ_a^M decreases
452 logarithmically with tumor size N , while the recurrence time τ_a^r is constant (Figure S8). Additionally, for large tumors, we have $M < N_m^* < N$, so the mean detection time is shorter compared to the mean
454 recurrence time, that is, the resistant tumor may be detected before recovering back to its initial size.

Discussion

456 We have modeled a tumor—a population of cancer cells—exposed to drug treatment that causes it to decline in size toward potential extinction. In this scenario, the tumor can be “evolutionarily rescued”
458 or escape extinction via two paths. In the direct path, a drug-sensitive cell acquires a mutation or aneuploidy that confers resistance and allows it to grow rapidly. In the indirect path, a sensitive cell
460 first becomes aneuploid, which diminishes the drug’s effect, and then an aneuploid cell acquires a mutation that confers resistance (Figure 1).

462 Using multi-type branching processes, we derived the probability of evolutionary rescue of the tumor under the effects of aneuploidy, ranging from tolerance to partial resistance. We obtained exact
464 and approximate expressions for the probability of evolutionary rescue (eq. (1)). Our results show that the probability of evolutionary rescue increases with the initial tumor size N , the drug-sensitive
466 growth rate Δ_s , the mutation rate ν , and the aneuploidy rate u .

When aneuploid cells are partially resistant to the drug ($\Delta_s \ll 0 \ll \Delta_a \ll \Delta_m$), aneuploidy
468 itself rescues the population (Figure 4A). When aneuploidy only provides tolerance to the drug ($\Delta_s \ll \Delta_a \ll 0 \ll \Delta_m$), it cannot rescue the population. Instead, it acts as a “stepping stone” through
470 which the resistant mutant can appear more rapidly, given that the number of aneuploid cells declines slower than the number of drug-sensitive cells (Figure 2). In this scenario, aneuploidy provides two
472 advantages. First, it delays the extinction of the population, providing more time for the appearance of the resistance mutation. Second, it increases the population size relative to a drug-sensitive population,
474 providing more cells in which mutations can occur. Together, this increases the cumulative number of mutants that arise (i.e., $Nuv\lambda_s\lambda_a/|\Delta_s\Delta_a|$).

476 We find that aneuploidy can significantly affect evolutionary rescue as it reduces the threshold tumor size by at least an order of magnitude even when aneuploidy only provides tolerance (Figure 3).
478 When the number of cells in the tumor is large enough (i.e., $N \gg N_m^* \approx 4 \times 10^7$), a resistance mutation will occur in drug-sensitive cells before these cells become extinct (Figure 3). Therefore,
480 large tumors are likely to be rescued with or without aneuploidy. However, anti-cancer drugs are often used as adjuvant therapy after resection, in which case the number of cells in the tumor may be below
482 the detection threshold of $\sim 10^7$ (Bozic et al., 2013). In these cases, aneuploidy can have a crucial role in the evolutionary rescue of the tumor and, therefore, in cancer recurrence. Indeed, secondary
484 tumors are estimated to cause the majority of cancer-related deaths (Chaffer and Weinberg, 2011). The importance of aneuploidy in the evolutionary rescue of secondary tumors is reinforced by the fact
486 that metastases have been shown to have a chromosome missegregation rate two to three orders of magnitude higher compared to primary tumors (Kimmel et al., 2023).

488 We compared the probability of evolutionary rescue in melanoma cells and triple-negative breast cancer cells (TNBC) under drug therapy (black and color lines, respectively, in Figure 3B).
490 This comparison suggests that TNBC has a higher probability of relapsing compared to melanoma,

because smaller tumors have higher rescue probability. Indeed, the probability of relapse in TNBC
492 patients is higher than 50% in the first 3-5 years after diagnosis (Taushanova et al., 2023), whereas in
melanoma patients it is approximately 10-20% in the first 5 years (Von Schuckmann et al., 2019, Wan
494 et al., 2022).

Given that the mean time for secondary tumors to adapt to anti-cancer drugs can be of the order
496 of 1,000 days (Figure S2A), aneuploidy can explain the reappearance of cancer even after initial
remission. The theoretical prediction for the mean rescue time of tumors smaller than 10^8 cells
498 is greater than 4 years, consistent with previous estimates of the recurrence time of tumors after
resection (Avanzini and Antal, 2019). We found that aneuploidy complements evolutionary rescue
500 through direct mutation because it produces rescue mutations mostly after the number of sensitive
cells has decreased to a point where a direct mutation is no longer a feasible option for evolutionary
502 rescue (Figure 6A).

We hypothesized that standing genetic variation (the existence of aneuploid cancer cells in the
504 tumor before the onset of therapy) could facilitate evolutionary rescue by reducing the waiting time
for the appearance of aneuploid cells. We found that a drug that reduces the sensitive growth rate and
506 does not significantly increase the chromosome missegregation rate will likely lead to evolutionary
rescue through standing genetic variation (Figure 5 and eq. (5)). Furthermore, if the fraction of
508 tumor cells that have the beneficial aneuploidy is $f \gg u\lambda_s/|\Delta_s| \approx 2.5\%$, then evolutionary rescue is
more likely to occur via standing variation rather than through *de novo* aneuploidy. However, for the
510 parameter values we focus on in our examples (Table 1), this fraction is an order of magnitude lower,
and therefore, we expect evolutionary rescue to occur by *de novo* aneuploidy.

Comparing our results to the evolutionary rescue literature, we complement the studies by Iwasa
512 et al. (2003) and Osmond et al. (2020) on multi-step rescue by deriving simple approximations for a
different fitness landscape. Similar to Osmond et al. (2020), we find that two-step rescues can be more
514 likely than simple one-step rescues. The “stationary” scenario, in which the aneuploid growth rate is
close to zero in the presence of drug, is particularly interesting. Although this may seem like a small
516 region of parameter space in a general model of evolutionary rescue (Fig. 4A, inset), the example of
certain aneuploidies in cancer suggests it could be biologically significant.
518

Experiments could test our model predictions. For example, to assess the effect of initial tumor
520 size on the probability of evolutionary rescue, a large culture mass can be propagated from a single
cancer cell in permissive conditions and then diluted to a range of starting tumor sizes. Then, the
522 extinction or survival of these tumors can be monitored during exposure to anti-cancer drugs that
induce aneuploidy or to saline solution for control (Ippolito et al., 2021). We can then compare the
524 results of these experiments to predictions of our model to see if tumors with initial size below the
threshold eq. (3) are more likely to become extinct due to drug exposure.

We have assumed that cancer cell lineages are independent and have verified that this is accurate
526 under simple logistic growth. However, this assumption neglects the potential effects of spatial
structure and local interactions, which may be important in solid tumors. Such tumors can be spatially
528 heterogeneous, with different genotypes inhabiting cellular niches and immune infiltration impacting
growth in affected regions (Galon et al., 2010, Varrone et al., 2023). This can potentially impact the
530 probability of evolutionary rescue (Martens et al., 2011). Furthermore, loss of extra-chromosome
may occur at a high rate (for estimates in yeast, see Hose et al. (2024)) and the fitness of a euploid
532 cell with a resistance mutation may be higher than that of an aneuploid cell with the same mutation.
Future work could test when these effects have significant effect on the results of our model. In
534 addition, our model can be applied to study evolutionary rescue in other biological systems, such as
evolution of yeast populations under different stress conditions (Kohanovski et al., 2024, Pompei and
536 Cosentino Lagomarsino, 2023).

538 **Conclusions.** Our results quantitatively suggest that aneuploidy may play an important role in tumor
adaptation to anti-cancer drugs when the tumor size is small or intermediate. Large tumors are
540 predicted to adapt to anti-cancer drugs through direct mutation. In contrast, smaller tumors are
predicted to become resistant either directly by aneuploidy or by a resistance mutation occurring in
542 aneuploid cells that serve as evolutionary “stepping stones” (Figure 3). Thus, therapies that increase
the rate of aneuploidy in tumors to combat cancer may also promote drug resistance.

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| | Name | Value | Units | References |
|-------------|---|---------------------------------------|-----------------|--|
| N | Initial tumor size | $10^7 - 10^9$ | cells | Del Monte (2009) |
| λ_s | Sensitive division rate | 0.1 | 1/days | Bozic et al. (2013), Rew and Wilson (2000) |
| μ_s | Sensitive death rate | 0.11 – 0.17 | 1/days | Bozic et al. (2013) |
| λ_a | Aneuploid division rate* | 0.06 – 0.1 | 1/days | - |
| μ_a | Aneuploid death rate* | 0.09 | 1/days | - |
| λ_m | Mutant division rate | 0.1 | 1/days | Bozic et al. (2013), Rew and Wilson (2000) |
| μ_m | Mutant death rate | 0.09 | 1/days | Bozic et al. (2013), Carlson (2003) |
| u | Misseggregation rate | 10^{-2} | 1/cell division | Lee et al. (2016) |
| v | Mutation rate | $10^{-9} - 10^{-7}$ | 1/cell division | Bozic et al. (2013), Loeb (2001) |
| \tilde{u} | Misseggregation rate in the drug free environment* | $5 \times 10^{-4} - 2 \times 10^{-2}$ | 1/cell division | Shi and King (2005), Thompson and Compton (2008) |
| c | Selection coefficient against aneuploidy in the drug free environment | 0.07 | 1/days | Lukow et al. (2021) |

Table 1: Model parameters: Melanoma. Parameters from Bozic et al. (2013) consider patients with melanoma treated with the anti-cancer drug vemurfenib, in which resistance is conferred by trisomy in either Chr 2 or Chr 6. We have modified the parameters from Bozic et al. (2013) such that sensitive and mutant division rates are $\lambda_s = \lambda_m = \log(2)/T \approx 0.1$ instead of their value of 0.14 where T is the doubling time in the absence of cellular death obtained from Rew and Wilson (2000). For a discussion of the different interpretations of the tumor doubling times see Avanzini and Antal (2019). Parameters marked with * are not obtained from the literature.

Appendices

Appendix A Survival probability of a single lineage

To analyze evolutionary rescue in our model, we use the framework of *multi-type branching processes* (Harris, 1963, Weissman et al., 2009). In the case of cancer, where all reproduction is binary fission, these branching processes are also *birth-death processes* (Kendall, 1948). This allows us to find explicit expressions for the *survival probability*: the probability that a lineage descended from a single cell does not become extinct.

Let p_s , p_a , and p_m be the survival probabilities of a population consisting initially of single sensitive cell, aneuploid cell, or mutant cell, respectively. The complements $1 - p_s$, $1 - p_a$, and $1 - p_m$

| | Name | Value | Units | References |
|-------------|-------------------------|-------------------|--------|---|
| λ_s | Sensitive division rate | 0.08 | 1/days | Salehi et al. (2021) |
| μ_s | Sensitive death rate | 0.0825, 0.1, 0.12 | 1/days | Salehi et al. (2021) |
| λ_a | Aneuploid division rate | 0.0845 | 1/days | Rew and Wilson (2000), Spratt et al. (1996) |
| μ_a | Aneuploid death rate | 0.076 | 1/days | Rew and Wilson (2000), Spratt et al. (1996) |

Table 2: Model parameters: Breast cancer. Parameters not listed here remain unchanged from the values provided in table 1.

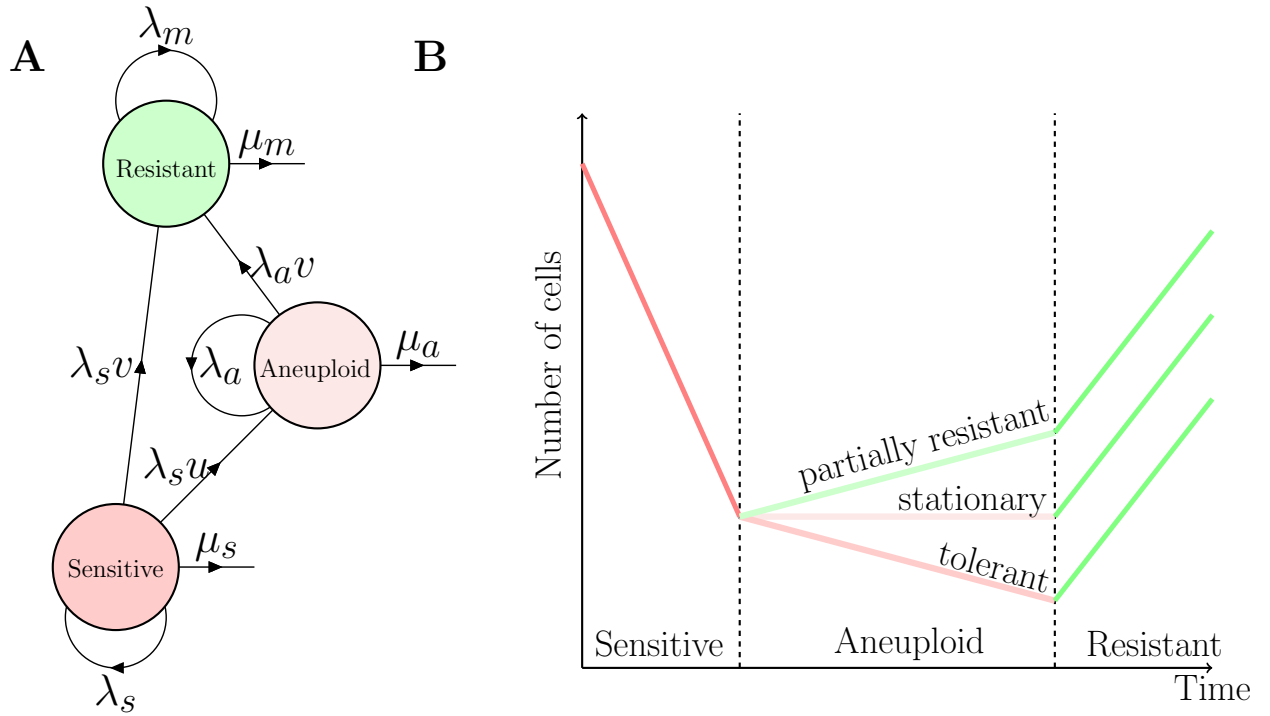


Figure 1: Model illustration. (A) A population of cancer cells is composed of drug-sensitive, aneuploid, and mutant cells, which divide with rates λ_s , λ_a , and λ_m and die at rates μ_s , μ_a , and μ_m , respectively. Sensitive cells can divide and become aneuploid at rate $u\lambda_s$. Both aneuploid and sensitive cells can divide and acquire a mutation with rates $v\lambda_a$ and $v\lambda_s$, respectively. Color denotes the relative growth rates of the three genotypes such that $\lambda_s - \mu_s < \lambda_a - \mu_a < \lambda_m - \mu_m$. (B) Sensitive cells are sensitive to the drug, while mutant cells are drug-resistant. The aneuploid may be tolerant, stationary, or partially resistant.

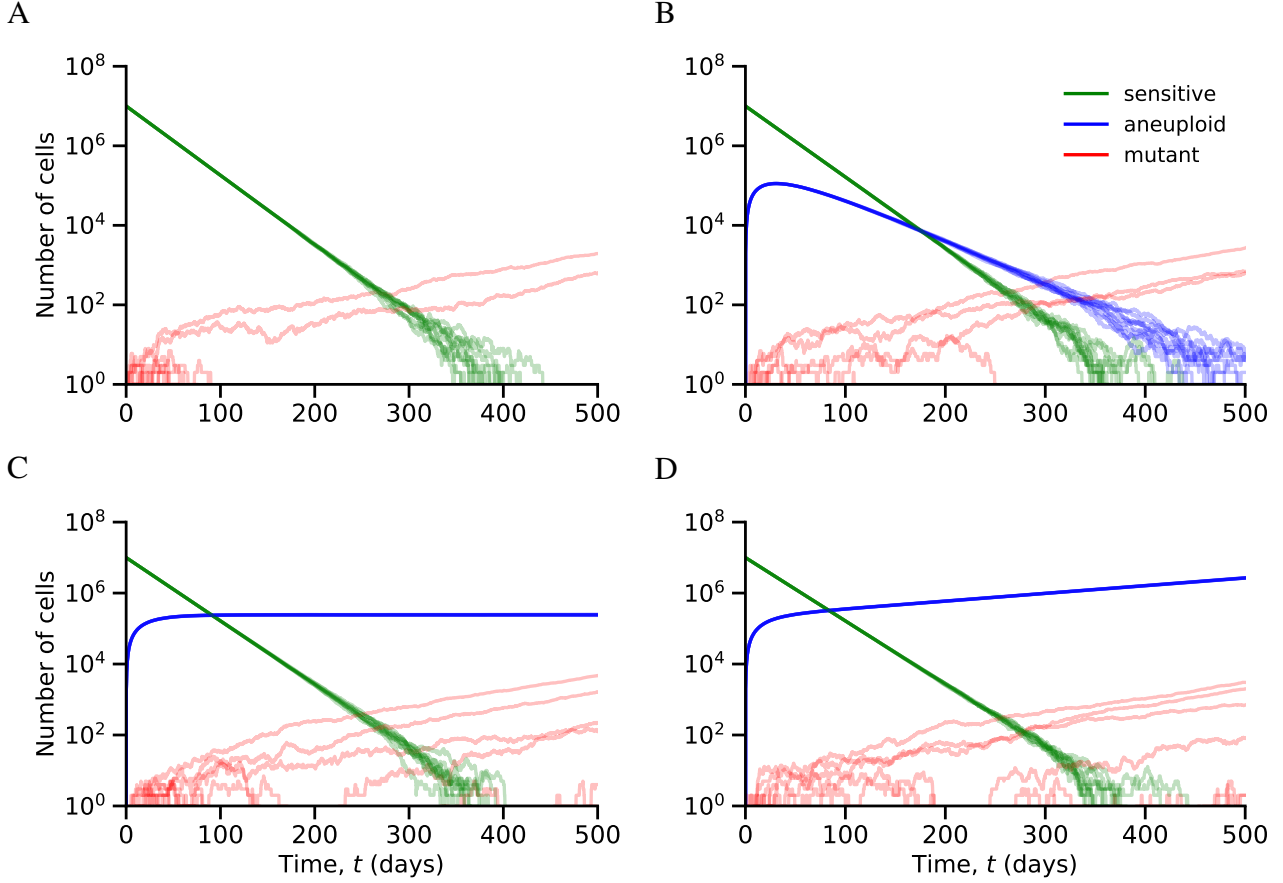
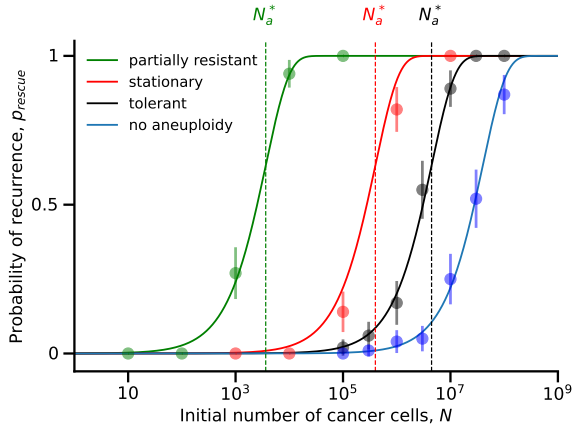


Figure 2: Sample trajectories of the genotype frequencies. (A) Without aneuploidy ($u = 0$), evolutionary rescue is possible through direct mutation, and in most scenarios, the tumor will become extinct due to the drug. (B) When aneuploid cells are tolerant ($\Delta_a < 0$) evolutionary rescue can occur indirectly, but direct mutation is the most likely path for evolutionary rescue. (C) When aneuploid cells are stationary ($\Delta_a \approx 0$), we observe the appearance of mutant lineages even after the sensitive population has gone extinct, thus showing that stationary aneuploidy increases the probability of evolutionary rescue. (D) When aneuploid cells are partially resistant ($\Delta_a > 0$), the tumor is rescued by the aneuploid cell population. Each plot shows 10 simulations of the number of sensitive, aneuploid, and mutant cells (s_t, a_t, m_t) over time t . Here, $\lambda_s = 0.1$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $\nu = 10^{-7}$, $N = 10^7$; (A) $u = 0$; (B) $\lambda_a = 0.065$, $u = 10^{-2}$; (C) $\lambda_a = 0.08999$, $u = 10^{-2}$; (D) $\lambda_a = 0.095$, $u = 10^{-2}$.

A



B

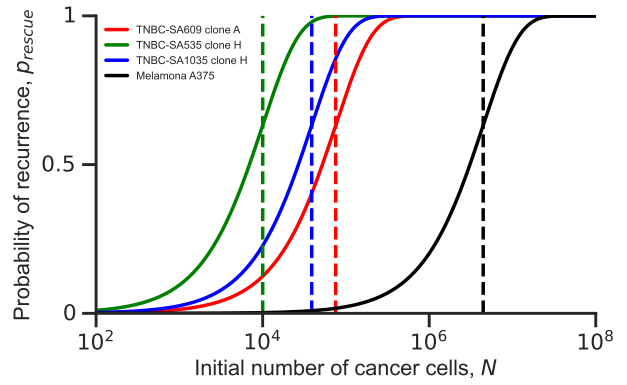
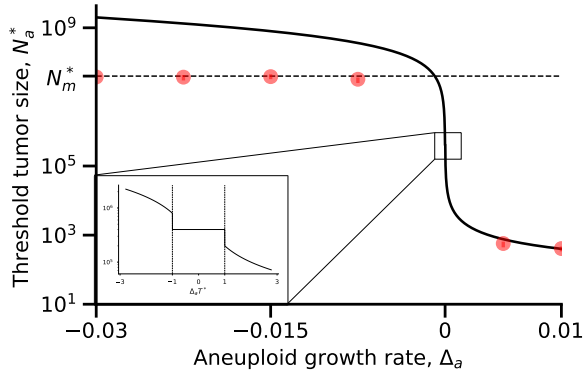


Figure 3: Aneuploidy facilitates the evolutionary rescue of cancer under drug treatment. The probability of evolutionary rescue, p_{rescue} , as a function of the initial tumor size, N (eq. (1)). Dashed vertical lines show the threshold tumor size, N_a^* , above which the probability is very high (eq. (3)). **(A)** Blue dashed line: without aneuploidy ($u = 0$). Black line: tolerant aneuploidy ($u = 10^{-2}$, $\lambda_a = 0.0899$). Red line: stationary aneuploidy ($u = 10^{-2}$, $\lambda_a = 0.0899$). Green line: partially resistant aneuploidy ($u = 10^{-2}$, $\lambda_a = 0.095$). Markers and error bars for averages of simulation results with 95% confidence interval ($p \pm 1.96\sqrt{p(1-p)/n}$ where p is the fraction of simulations in which the tumor has been rescued, and $n = 100$ is the number of simulations). Parameters: $\lambda_s = 0.1$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $v = 10^{-7}$. **(B)** Comparison for melanoma (black) and breast cancer (colors) with parameters from the literature (Tables 1 and 2). Black line: Melanoma A375. Blue line: Breast cancer TNBC-SA1035 clone H. Red line: Breast cancer TNBC-SA609 clone A. Green line: Breast cancer TNBC-SA535 clone H.

A



B

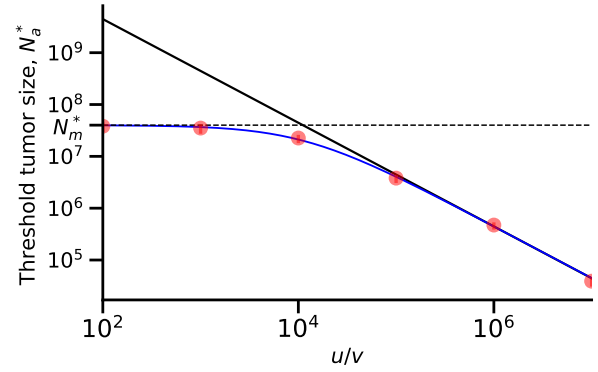


Figure 4: The effect of aneuploidy on tumor threshold size. (A) The threshold tumor size N_a^* (eq. (3)) as a function of the aneuploid growth rate Δ_a . The dashed horizontal line shows N_m^* (eq. (2)), the threshold tumor size without aneuploidy ($u = 0$). When aneuploid growth rate is close to or higher than zero, aneuploidy decreases the threshold tumor size, facilitating evolutionary rescue. The inset highlights the scenario when aneuploid cells are stationary. Red dots for simulations and error bars for the 95% confidence intervals obtained with bootstrap (Appendix G). Parameters: $\lambda_s = 0.1, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}$. (B) Threshold tumor size N_a^* (eq. (3)) as a function of the ratio of aneuploidy and mutation rates, u/v . Dashed horizontal line shows N_m^* (eq. (2)), the threshold tumor size without aneuploidy ($u = 0$). When the aneuploidy rate is much higher than the mutation rate, aneuploidy decreases the threshold tumor size, facilitating evolutionary rescue. Blue line represents the exact formula for threshold tumor size N_a^* while the solid black line represents the approximation (eq. (3)). Red dots represent simulation results, and the error bars represent the 95% confidence intervals obtained with bootstrap (Appendix G). Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, v = 10^{-7}$.

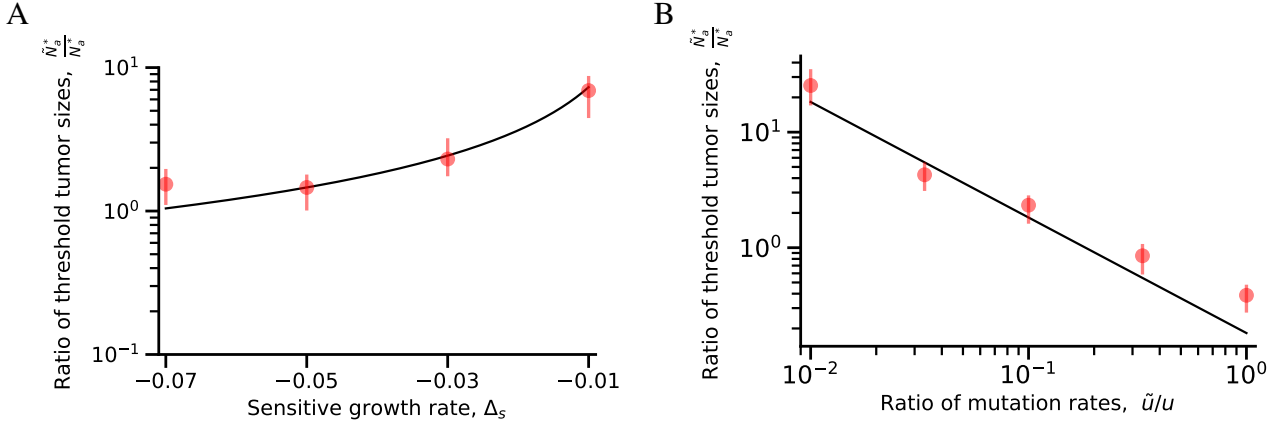


Figure 5: Standing genetic variation facilitates the evolutionary rescue of cancer. (A) Ratio of threshold tumor sizes for rescue by standing genetic variation and by *de novo* variation, \tilde{N}_a^*/N_a^* , when a fraction $\frac{\tilde{u}\lambda_s}{c}$ is aneuploid at the start of treatment, as a function of the sensitive growth rate Δ_s . Standing genetic variation will drive adaptation to the drug if the sensitive population is rapidly declining ($\Delta_s \ll 0$) due to a stronger effect of the drug on sensitive cells. Red dots represent simulation results, and the error bars represent the 95% confidence intervals obtained with bootstrap (Appendix G). Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_a = 0.09, \mu_m = 0.09, \tilde{u} = 10^{-3}, u = 10^{-2}, v = 10^{-7}$. (B) Ratio of threshold tumor size \tilde{N}_a^* , when a fraction $\frac{\tilde{u}\lambda_s}{c}$ is aneuploid at the start of treatment, and N_a^* as a function of the ratio of aneuploidy rates \tilde{u}/u . *De novo* aneuploids will have a larger contribution to the appearance of drug resistance if the drug induces the appearance of aneuploid cells ($u \gg \tilde{u}$). Red dots represent simulation results, and the error bars represent the 95% confidence intervals obtained with bootstrap (Appendix G). Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, \tilde{u} = 10^{-3}, v = 10^{-7}$.

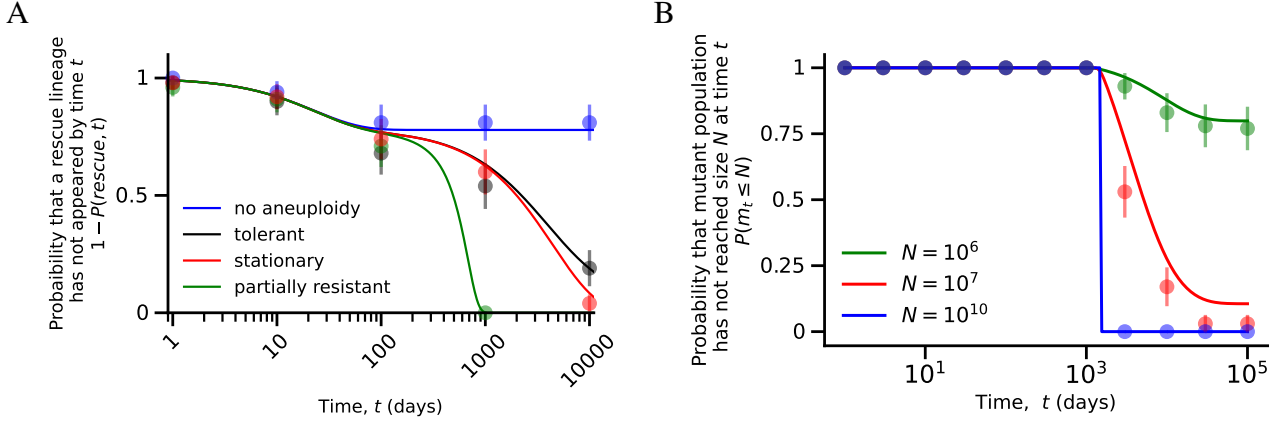


Figure 6: Aneuploidy extends the window of opportunity for evolutionary rescue. (A) The probability that a successful mutant has not appeared by time t . Black line: tolerant aneuploidy ($u > 0, \lambda_a = 0.0899$). Red line: stationary aneuploidy ($u > 0, \lambda_a = 0.089999$). Green line: partially resistant aneuploidy ($u > 0, \lambda_a = 0.095$). Blue line: no aneuploidy ($u = 0$). Aneuploidy plays an important role in rescuing the tumor cell population as the sensitive population becomes extinct. Markers represent simulation results, and the error bars represent 95% confidence interval ($p \pm 1.96\sqrt{p(1-p)/n}$ where p is the fraction of simulations in which a successful mutant has not been generated, and $n = 100$ is the number of simulations). Parameters: $\lambda_s = 0.1, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}, N = 10^7$. (B) Probability that a mutant cancer cell population has not reached size N at time t . Green line: $N = 10^6$ (small tumor). Red line: $N = 10^7$ (intermediate-sized tumor). Blue line: $N = 10^{10}$ (large tumor). Increasing the initial tumor size guarantees that the cancer will relapse. Markers represent simulations, and the error bars represent 95% confidence interval ($p \pm 1.96\sqrt{p(1-p)/n}$ where p is the fraction of the simulations in which the mutant population size has not reached N and $n = 100$ is the number of simulations). Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}$.

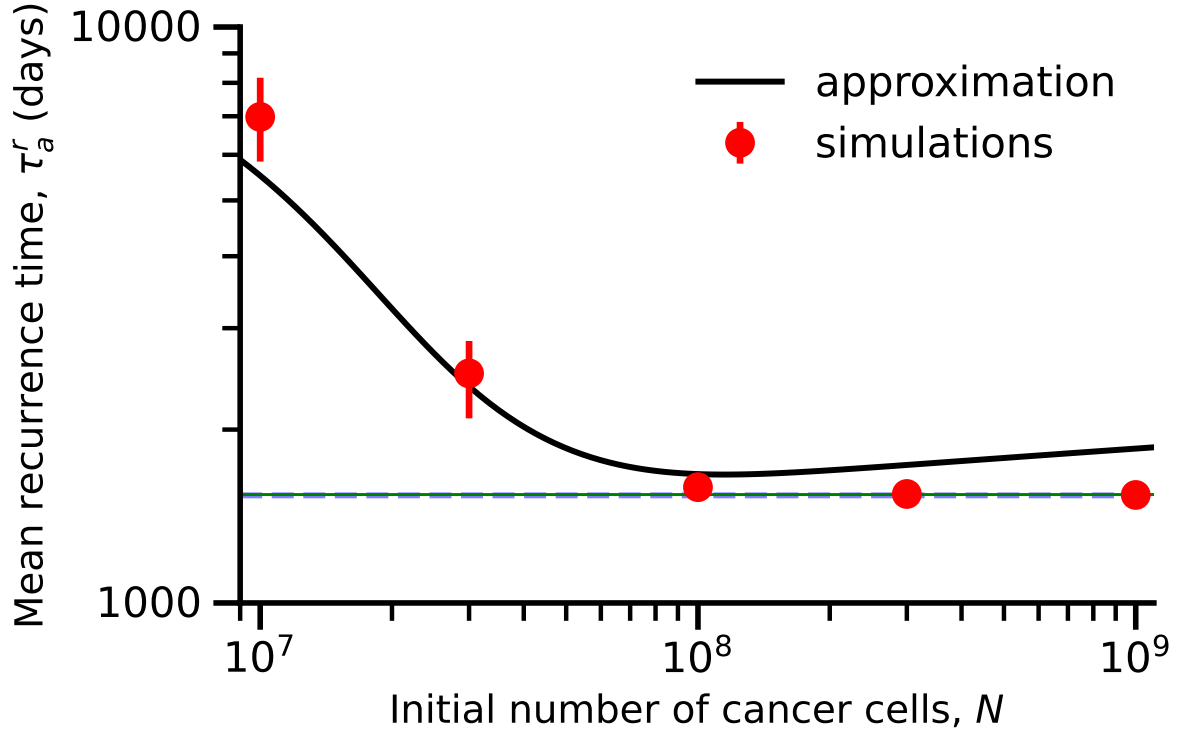


Figure 7: Tumor size decreases the mean recurrence time. The mean time for the mutant cell population to reach size N , the initial number of cancer cells. Our inhomogeneous Poisson-process approximation (solid black line, eq. (D1)) is in agreement with simulation results (red markers with error bars for 95% CI) for intermediate size N . Simulation results converge to eq. (D4) (blue dashed line) for large values of N . The green line represents the numerical solution of eq. (D3). Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}$.

are the extinction probabilities, which satisfy each its respective equation (Harris, 1963),

$$\begin{aligned}
1 - p_s &= \frac{\mu_s}{\lambda_s + \mu_s + u\lambda_s + v\lambda_s} + \frac{u\lambda_s}{\lambda_s + \mu_s + u\lambda_s + v\lambda_s} (1 - p_a) (1 - p_s) + \\
&\quad \frac{\lambda_s}{\lambda_s + \mu_s + u\lambda_s + v\lambda_s} (1 - p_s)^2 + \frac{v\lambda_s}{\lambda_s + \mu_s + u\lambda_s + v\lambda_s} (1 - p_m) (1 - p_s), \\
1 - p_a &= \frac{\mu_a}{\lambda_a + \mu_a + v\lambda_a} + \frac{v\lambda_a}{\lambda_a + \mu_a + v\lambda_a} (1 - p_m) (1 - p_a) + \frac{\lambda_a}{\lambda_a + \mu_a + v\lambda_a} (1 - p_a)^2, \\
1 - p_m &= \frac{\mu_m}{\lambda_m + \mu_m} + \frac{\lambda_m}{\lambda_m + \mu_m} (1 - p_m)^2.
\end{aligned} \tag{A1}$$

The survival probabilities are given by the smallest solution for each quadratic equation (Uecker et al., 2015). Therefore we have

$$\begin{aligned}
p_s &= \frac{\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m + \sqrt{(\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m)^2 + 4\lambda_s^2 (u p_a + v p_m)}}{2\lambda_s}, \\
p_a &= \frac{\lambda_a - \mu_a - v\lambda_a p_m + \sqrt{(\lambda_a - \mu_a - v\lambda_a p_m)^2 + 4\lambda_a^2 v p_m}}{2\lambda_a}, \\
p_m &= \frac{\lambda_m - \mu_m}{\lambda_m}.
\end{aligned} \tag{A2}$$

Note that the equation for p_s depends on both p_a and p_m , and the equation for p_a depends on p_m . To proceed, we can plug the solution for p_m and p_a into the solution for p_s . We perform this for three different scenarios.

Scenario 1: Aneuploid cells are partially resistant

We first assume that aneuploidy provides partial resistance to drug therapy, $\lambda_a > \mu_a$, and that this resistance is significant, $(\lambda_a - \mu_a - v\lambda_a p_m)^2 > 4\lambda_a^2 v p_m$. We thus rewrite eq. (A2) as

$$\begin{aligned}
p_s &= \frac{\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m}{2\lambda_s} \left(1 - \sqrt{1 + \frac{4\lambda_s^2 (v p_m + u p_a)}{(\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m)^2}} \right), \text{ and} \\
p_a &= \frac{\lambda_a - \mu_a - v\lambda_a p_m}{2\lambda_a} \left(1 + \sqrt{1 + \frac{4\lambda_a^2 v p_m}{(\lambda_a - \mu_a - v\lambda_a p_m)^2}} \right).
\end{aligned}$$

Using the Taylor expansion $\sqrt{1+x} = 1 + x/2 + \mathcal{O}(x^2)$ and assuming $u, v \ll 1$, we obtain the following approximation for the survival probability of a population initially consisting of a single sensitive cell,

$$\begin{aligned}
p_s &\approx -\frac{v\lambda_s p_m + u\lambda_s p_a}{\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m} \\
&\approx -\frac{1}{\lambda_s - \mu_s} \left[\frac{u\lambda_s (\lambda_a - \mu_a)}{\lambda_a} + \frac{uv\lambda_s \lambda_a (\lambda_m - \mu_m)}{\lambda_m (\lambda_a - \mu_a)} + \frac{v\lambda_s (\lambda_m - \mu_m)}{\lambda_m} \right].
\end{aligned} \tag{A3}$$

Now uv is very small, and if we use the fact that $v \ll u$, we have:

$$p_s \approx \frac{u\lambda_s \Delta_a}{|\Delta_s| \lambda_a}. \tag{A4}$$

However, if aneuploidy is very rare such that

$$\frac{u\lambda_s\Delta_a}{\lambda_a} < \frac{v\lambda_s\Delta_m}{\lambda_m} \Rightarrow u\lambda_a < \frac{v\lambda_a^2\Delta_m}{\lambda_m} \frac{1}{\Delta_a} < \frac{v\lambda_a^2\Delta_m}{\lambda_m} \frac{1}{\sqrt{4\lambda_a^2vp_m}} \Rightarrow u\lambda_a < T^*,$$

where $T^* = (4v\lambda_a^2\Delta_m/\lambda_m)^{-1/2}$ and in the second inequality we used the fact that $\Delta_a^2 > 4\lambda_a^2vp_m$. In this scenario adaptation is through direct mutation and:

$$p_s \approx \frac{v\lambda_s}{|\Delta_s|} \frac{\Delta_m}{\lambda_m}.$$

Scenario 2: Aneuploid cells are tolerant.

We now assume that aneuploidy provides tolerance to drug therapy, that is, the number of aneuploid cells significantly declines over time, but at a lower rate than the number of sensitive cells, $\lambda_s - \mu_s < \lambda_a - \mu_a < 0$. We also assume that the decline is significant, $(\lambda_a - \mu_a - v\lambda_ap_m)^2 > 4\lambda_a^2vp_m$. We rewrite eq. (A2) as

$$\begin{aligned} p_s &= \frac{\lambda_s - \mu_s - u\lambda_sp_a - v\lambda_sp_m}{2\lambda_s} \left(1 - \sqrt{1 + \frac{4\lambda_s^2(vp_m + up_a)}{(\lambda_s - \mu_s - u\lambda_sp_a - v\lambda_sp_m)^2}} \right), \\ p_a &= \frac{\lambda_a - \mu_a - v\lambda_ap_m}{2\lambda_a} \left(1 - \sqrt{1 + \frac{4\lambda_a^2vp_m}{(\lambda_a - \mu_a - v\lambda_ap_m)^2}} \right). \end{aligned} \quad (\text{A5})$$

Since $u, v \ll 1$, the term in the root can be approximated using a Taylor expansion. So, substituting the expressions for p_a and p_m , we have

$$\begin{aligned} p_s &\approx -\frac{v\lambda_sp_m + u\lambda_sp_a}{\lambda_s - \mu_s - u\lambda_sp_a - v\lambda_sp_m} \\ &\approx \frac{1}{\lambda_s - \mu_s - u\lambda_sp_a - v\lambda_sp_m} \left[\frac{uv\lambda_s\lambda_a(\lambda_m - \mu_m)}{\lambda_m(\lambda_a - \mu_a - v\lambda_a)} - \frac{v\lambda_s(\lambda_m - \mu_m)}{\lambda_m} \right] \\ &\approx \frac{v\lambda_s(\lambda_m - \mu_m)}{\lambda_m(\lambda_s - \mu_s)} \left[\frac{u\lambda_a}{(\lambda_a - \mu_a)} - 1 \right] \\ &= \frac{v\lambda_s\Delta_m}{\lambda_m|\Delta_s|} \left(\frac{u\lambda_a}{|\Delta_a|} + 1 \right). \end{aligned} \quad (\text{A6})$$

If we assume that aneuploidy is not rare ($u\lambda_a > |\Delta_a|$) then we have:

$$p_s \approx \frac{u\lambda_s}{|\Delta_s|} \frac{v\lambda_a}{|\Delta_a|} \frac{\Delta_m}{\lambda_m}. \quad (\text{A7})$$

Scenario 3: Aneuploid cells are stationary

We now assume that the growth rate of aneuploid cells is close to zero (either positive or negative), such that $(\Delta_a - v\lambda_ap_m)^2 \ll 4\lambda_a^2vp_m$. We rewrite eq. (A2) as

$$p_a = \frac{\lambda_a - \mu_a - v\lambda_ap_m + 2\sqrt{\lambda_a^2vp_m} \left(1 + \frac{(\lambda_a - \mu_a - v\lambda_ap_m)^2}{4\lambda_a^2vp_m} \right)^{\frac{1}{2}}}{2\lambda_a}. \quad (\text{A8})$$

Using a following Taylor series expansion for small $(\lambda_a - \mu_a - v\lambda_a p_m)^2 / 4\lambda_a^2 v p_m$,

$$\left(1 + \frac{(\lambda_a - \mu_a - v\lambda_a p_m)^2}{4\lambda_a^2 v p_m}\right)^{\frac{1}{2}} = 1 + \frac{(\lambda_a - \mu_a - v\lambda_a p_m)^2}{8\lambda_a^2 v p_m} + \dots,$$

we obtain the approximation

$$\begin{aligned} p_a &\approx \frac{\lambda_a - \mu_a - v\lambda_a p_m + 2\sqrt{\lambda_a^2 v p_m} \left[1 + \frac{(\lambda_a - \mu_a - v\lambda_a p_m)^2}{8\lambda_a^2 v p_m}\right]}{2\lambda_a} \\ &= \frac{\lambda_a - \mu_a - v\lambda_a p_m + 2\sqrt{\lambda_a^2 v p_m} + \frac{(\lambda_a - \mu_a - v\lambda_a p_m)^2}{4\sqrt{\lambda_a^2 v p_m}}}{2\lambda_a} \\ &= \frac{(\lambda_a - \mu_a - v\lambda_a p_m + 2\sqrt{\lambda_a^2 v p_m})^2 + 4\lambda_a^2 v p_m}{8\lambda_a \sqrt{\lambda_a^2 v p_m}} \\ &= \frac{4\lambda_a^2 v p_m + 4\lambda_a^2 v p_m \left(1 + \frac{\lambda_a - \mu_a - v\lambda_a p_m}{2\sqrt{\lambda_a^2 v p_m}}\right)^2}{8\lambda_a \sqrt{\lambda_a^2 v p_m}} \\ &= \frac{1}{2\lambda_a} \left(\lambda_a - \mu_a - v\lambda_a p_m + 2\sqrt{\lambda_a^2 v p_m}\right). \end{aligned} \tag{A9}$$

Plugging this in eq. (A3), the survival probability of a population starting from one sensitive cell is

$$\begin{aligned} p_s &\approx -\frac{1}{\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m} \left[v\lambda_s \frac{\lambda_m - \mu_m}{\lambda_m} + \frac{u\lambda_s}{2\lambda_a} \left(\lambda_a - \mu_a - v\lambda_a p_m + 2\sqrt{\lambda_a^2 v p_m}\right) \right] \\ &= -\frac{1}{\lambda_s - \mu_s - u\lambda_s p_a - v\lambda_s p_m} \left[v\lambda_s \frac{\lambda_m - \mu_m}{\lambda_m} + \frac{u\lambda_s}{2\lambda_a} (\lambda_a - \mu_a - v\lambda_a p_m) + u\lambda_s \sqrt{\frac{v(\lambda_m - \mu_m)}{\lambda_m}} \right] \\ &\approx -\frac{1}{\Delta_s} \left[v\lambda_s \frac{\Delta_m}{\lambda_m} + \frac{u\lambda_s (\Delta_a - v\lambda_a p_m)}{2\lambda_a} + u\lambda_s \sqrt{\frac{v\Delta_m}{\lambda_m}} \right]. \end{aligned} \tag{A10}$$

Using the fact that

$$(\Delta_a - v\lambda_a p_m)^2 \ll 4\lambda_a^2 v p_m \Rightarrow \frac{\Delta_a - v\lambda_a p_m}{2\lambda_a} \ll \sqrt{\frac{v\lambda_a \Delta_m}{\lambda_m}},$$

and $v \ll u$ we obtain:

$$p_s \approx \frac{u\lambda_s}{|\Delta_s|} \sqrt{\frac{v\lambda_a \Delta_m}{\lambda_m}}. \tag{A11}$$

Appendix B Evolutionary rescue probability

Using the fact that $\Delta_a - v\lambda_a p_m \approx \Delta_a$ we write the condition $(\Delta_a - v\lambda_a p_m)^2 \ll 4\lambda_a^2 v p_m$ as:

$$\Delta_a^2 \ll 4\lambda_a^2 v p_m \Rightarrow -1 \ll \Delta_a T^* \ll 1,$$

where $T^* = (4v\lambda_a^2\Delta_m/\lambda_m)^{-1/2}$. Substituting eqs. (A4), (A7) and (A11) into eq. (1), the evolutionary rescue probability can be approximated by

$$p_{\text{rescue}} \approx \begin{cases} 1 - \exp\left[-\frac{u\lambda_a}{|\Delta_s|} \frac{v\lambda_s}{|\Delta_a|} \frac{\Delta_m}{\lambda_m} N\right], & \Delta_a T^* \ll -1, \\ 1 - \exp\left[-\frac{u\lambda_s}{|\Delta_s|} \sqrt{\frac{v\lambda_a\Delta_m}{\lambda_m}} N\right], & -1 \ll \Delta_a T^* \ll 1, \\ 1 - \exp\left[-\frac{u\lambda_s}{|\Delta_s|} \frac{\Delta_a}{\lambda_a} N\right], & 1 \ll \Delta_a T^*. \end{cases} \quad (\text{B1})$$

Appendix C Evolutionary rescue time

We first calculate the expected time for the appearance of the first mutant that rescues the cell population. This can occur either through the evolutionary trajectory *sensitive*→*mutant* or through the trajectory *sensitive*→*aneuploid*→*mutant*. We start with the former.

Assuming no aneuploidy ($u = 0$), we define T_m to be the time at which the first mutant cell appears that will avoid extinction and will therefore rescue the population. Note that if extinction occurs, that is the frequency of mutants after a very long time is zero, $m_\infty = 0$, then it is implied that $T_m = \infty$, and vice versa if $T_m < \infty$ then $m_\infty > 0$.

The number of successful mutants generated until time t can be approximated by an inhomogeneous Poisson process with rate $R_m(t) = v\lambda_s p_m s_t$, where $s_t = Ne^{\Delta_s t}$ is the number of sensitive cells at time t . Note that

$$\int_0^t R_m(z) dz = v\lambda_s p_m N \frac{\exp[\Delta_s t] - 1}{\Delta_s} \approx v\lambda_s p_m N t, \quad (\text{C1})$$

by integrating the exponential and because $\frac{1}{\Delta_s} (\exp[\Delta_s t] - 1) = t + O(\Delta_s t^2)$. The probability density function of T_m is thus $R_m(t) \exp\left(-\int_0^t R_m(z) dz\right)$ (Allen, 2010). Therefore, the probability density function of the conditional random variable ($T_m \mid T_m < \infty$) is $f_m(t) = R_m(t) \exp\left(-\int_0^t R_m(z) dz\right) / p_{\text{rescue}}$.

We are interested in the mean conditional time, $\tau_m = \mathbb{E}[T_m \mid T_m < \infty]$, which is given by

$$\tau_m = \int_0^\infty t f_m(t) dt = \frac{\int_0^\infty t R_m(t) \exp\left(-\int_0^t R_m(z) dz\right) dt}{p_{\text{rescue}}}, \quad (\text{C2})$$

Therefore, plugging eqs. (1) and (C1) in eq. (C2),

$$\tau_m = \int_0^\infty t v\lambda_s N e^{\Delta_s t} \frac{e^{-v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s}}}{1 - (1 - p_s)^N} dt \approx \int_0^\infty t v\lambda_s N e^{\Delta_s t} \frac{e^{-v\lambda_s N p_m t}}{1 - e^{-N p_s}} dt. \quad (\text{C3})$$

Figure S2B shows the agreement between this approximation and simulation results.

Assuming aneuploidy is possible ($u > 0$), we define T_a to be the time at which the first mutant cell appears that will rescue the population. We are interested in the mean conditional time, $\tau_a = \mathbb{E}[T_a \mid T_a < \infty]$.

When $Nu\lambda_s/|\Delta_s| \gg 1$ the aneuploid frequency dynamics is roughly deterministic and therefore can be approximated by

$$a_t \approx \frac{Nu\lambda_s}{\Delta_s - \Delta_a} \left(e^{\Delta_s t} - e^{\Delta_a t} \right). \quad (\text{C4})$$

As a result, the number of successful mutants created by direct mutation and via aneuploidy can be approximated by inhomogeneous Poisson processes with the rates

$$r_1(t) = v\lambda_a p_m a_t,$$

$$r_2(t) = v\lambda_s p_m s_t,$$

and the expected number of successful mutants created by direct mutation and via aneuploidy until time t is given by:

$$M_a(t) = v\lambda_a p_m \int_0^t a_z dz = \frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a} \right), \quad (C5)$$

$$M_m(t) = v\lambda_s p_m \int_0^t s_z dz = v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s}. \quad (C6)$$

For large initial population sizes we assume that the two processes are independent and as a result, they can be merged into a single Poisson process with rate $R_a(t) = (r_1 + r_2)(t)$. Consequently, the mean time to the appearance of the first rescue mutant is

$$\begin{aligned} \tau_a &= \frac{\int_0^\infty t R_a(t) \exp\left(-\int_0^t R_a(z) dz\right) dt}{P_{\text{rescue}}} \\ &= \int_0^\infty t (v\lambda_a p_m a_t + v\lambda_s p_m s_t) \frac{\exp\left[-\frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a}\right) - v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s}\right]}{1 - e^{-N p_s}} dt, \end{aligned} \quad (C7)$$

which we plot in Figure S2A as a function of the initial population size, N .

Paradoxically, we observe from Figure S2 that the mean time of a rescue mutation to appear is significantly shorter for the scenario when $u = 0$ when compared to the scenario $u > 0$, however this can be explained by the fact this mean time is conditioned on evolutionary rescue and, as a result, aneuploidy increase the *window of opportunity* in which a rescue mutation could appear thus increasing the mean time as well (Figure 2).

Let N_a^* and N_m^* be the threshold population size above which evolutionary rescue through aneuploidy or direct mutation, respectively, is very likely. The mean time τ_a can be written as:

$$\begin{aligned} \tau_a &= \int_0^\infty t f(t) dt = \int_0^\infty t \frac{d}{dt} F(t) dt = - \int_0^\infty t \frac{d}{dt} S(t) dt \\ &= -[tS(t)]_0^\infty + \int_0^\infty S(t) dt \\ &= \int_0^\infty S(t) dt, \end{aligned}$$

where $f(t)$, $F(t)$ and $S(t)$ are the probability density function, cumulative distribution function and survival function. In our case, $S(t) = \exp\left(-\int_0^t R_a(z) dz\right)$. Additionally, for $N \gg N_m^*$ we have $1 - e^{-N p_s} \approx 1$ and, as a result, we have:

$$\tau_a = \int_0^\infty e^{-\int_0^t R_a(z) dz} dt = \int_0^\infty \exp\left[-\frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a}\right) - v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s}\right] dt,$$

and we use the following Taylor series expansions:

$$\frac{e^{\Delta_s t} - 1}{\Delta_s} = \frac{1 + \Delta_s t + O(t^2) - 1}{\Delta_s} = t + O(t^2),$$

$$\frac{e^{\Delta_a t} - 1}{\Delta_a} = \frac{1 + \Delta_a t + O(t^2) - 1}{\Delta_a} = t + O(t^2),$$

to obtain a simpler approximation for τ_a :

$$\tau_a \approx \int_0^\infty e^{-v\lambda_s N p_m t} dt = \frac{1}{v\lambda_s N p_m}. \quad (C8)$$

If $N \ll N_a^*$ then the probability distribution of evolutionary rescue time is skewed toward small values (i.e. evolutionary rescue occurs conditioned on it happening). As a result, we have:

$$\frac{e^{\Delta_s t} - 1}{\Delta_s} = \frac{1 + \Delta_s t + O((\Delta_s t)^2) - 1}{\Delta_s} = t + O(\Delta_s t^2)$$

$$\frac{e^{\Delta_a t} - 1}{\Delta_a} = \frac{1 + \Delta_a t + O((\Delta_a t)^2) - 1}{\Delta_a} = t + O(\Delta_a t^2)$$

We observe that the first term in the exponential in eq. (C7) can be approximated to be zero and the second term as $-v\lambda_s N p_m t$ where $t \ll 1$. As a result, we can approximate:

$$\exp \left[-\frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a} \right) - v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s} \right] \sim 1$$

Additionally, since $N \ll N_a^* \ll N_m^*$, evolutionary rescue is more likely to occur through the trajectory *sensitive* \rightarrow *aneuploid* \rightarrow *mutant*. As a result, we can write Equation (C7) as:

$$\tau_a \approx \frac{\int_0^\infty t v \lambda_a p_m a_t dt}{1 - e^{-N p_s}} \approx \frac{uv\lambda_a \lambda_s p_m |\Delta_s + \Delta_a|}{p_s \Delta_a^2 \Delta_s^2}$$

$$= \frac{1}{|\Delta_s|} + \frac{1}{|\Delta_a|}, \quad (C9)$$

where in the last line we used the fact that $1/p_s = N_a^*$ and Equation (3).

If a fraction f of the cancer cells are aneuploid when the drug is administered then the expected number of successful mutants generated until time t is given by:

$$r_1^f(t) = v\lambda_a p_m \int_0^t a_z dz = (1 - f) \frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a} \right) + f v\lambda_a N p_m \frac{e^{\Delta_a t} - 1}{\Delta_a},$$

$$r_2^f(t) = v\lambda_s p_m \int_0^t s_z dz = (1 - f) v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s},$$

and the mean evolutionary rescue time is given by:

$$\tilde{\tau}_a = \frac{\int_0^\infty t R_a^f(t) \exp \left(-\int_0^t R_a^f(z) dz \right) dt}{p_{\text{rescue}}}, \quad (C10)$$

where $R_a^f(t) = r_1^f(t) + r_2^f(t)$ and $p_{\text{rescue}} = 1 - \exp \left[-(1 - f) p_s N - f p_a N \right]$. We plot our approximation in Figure S9 together with simulated data.

Appendix D Recurrence time

We define the proliferation time τ_a^p to be the time it takes the population of mutant cancer cells to reach the initial tumor size N . The number of rescue lineages generated by the sensitive population is given by eq. (C5) (see Figure S3):

$$r_1(\infty) = \frac{uv\lambda_s\lambda_a N p_m}{|\Delta_s||\Delta_a|} = \frac{N}{N_a^*},$$

where we ignore lineages created by direct mutation because we assumed $u\lambda_a > \max(-\Delta_a, 1/T^*)$, $N \ll N_m^*$ and used Equation (3).

This helps us distinguish between two scenarios for the proliferation time. Firstly, when we have at most one lineages which rescues the cancer cell population:

$$N \ll N_a^*.$$

As a result, the recurrence time is given by (Avanzini and Antal, 2019):

$$\tau_a^r \approx \tau_a + \frac{\log p_m N}{\Delta_m}. \quad (D1)$$

The factor of p_m in the second term of eq. (D1) is due to the fact that the lineage is conditioned to survive genetic drift and the time to reach N is shorter then the scenario without this property (Orr and Unckless, 2014, Smith and Haigh, 1974).

The second scenario is when the sensitive population produces a large number of rescue lineages in a short period of time. This is given by the condition:

$$N \gg N_a^*.$$

As a result, the recurrence time is obtained by solving the following system of ODEs:

$$\begin{aligned} \frac{ds}{dt} &= \Delta_s s, \\ \frac{da}{dt} &= \Delta_a a + u\lambda_s s, \\ \frac{dm}{dt} &= \Delta_m m + v\lambda_a a + v\lambda_s s. \end{aligned} \quad (D2)$$

Solving the system of ODEs for initial condition $(s(0), a(0), m(0)) = (N, 0, 0)$ we obtain:

$$m(t) = \frac{Nuv\lambda_a\lambda_s}{\Delta_s - \Delta_a} \left[\frac{e^{\Delta_s t} - e^{\Delta_m t}}{\Delta_s - \Delta_m} - \frac{e^{\Delta_a t} - e^{\Delta_m t}}{\Delta_a - \Delta_m} \right] + Nv\lambda_s \frac{e^{\Delta_s t} - e^{\Delta_m t}}{\Delta_s - \Delta_m}.$$

We obtain τ_a^r such that $m(\tau_a^r) = N$ by solving:

$$1 = \frac{uv\lambda_a\lambda_s}{\Delta_s - \Delta_a} \left[\frac{e^{\Delta_s \tau_a^r} - e^{\Delta_m \tau_a^r}}{\Delta_s - \Delta_m} - \frac{e^{\Delta_a \tau_a^r} - e^{\Delta_m \tau_a^r}}{\Delta_a - \Delta_m} \right] + v\lambda_s \frac{e^{\Delta_s \tau_a^r} - e^{\Delta_m \tau_a^r}}{\Delta_s - \Delta_m}. \quad (D3)$$

This is a transcendental equation which cannot be solved exactly but we can obtain an approximation by noting that for large τ_a^r the above equation can be written as:

$$1 = v\lambda_s \frac{e^{\Delta_m \tau_a^r}}{|\Delta_s - \Delta_m|},$$

which has solution:

$$\tau_a^r \approx \frac{1}{\Delta_m} \log \frac{\Delta_m - \Delta_s}{v\lambda_s}. \quad (\text{D4})$$

We observe that the terms given by the evolutionary trajectory *sensitive* \rightarrow *aneuploid* \rightarrow *mutant* do not contribute to the above approximation and, as a result, we deduce that it is accurate only for $N \gg N_m^* > N_a^*$.

Additionally, we note that if we are interested in the time until the tumor reaches a detectable size M then our above analysis is valid but in Equation (D1) we change:

$$\tau_a^{r,M} \approx \tau_a + \frac{\log p_m M}{\Delta_m}, \quad (\text{D5})$$

and Equation (D4) becomes:

$$\tau_a^{r,M} \approx \frac{1}{\Delta_m} \log \frac{M (\Delta_m - \Delta_s)}{v\lambda_s N}, \quad (\text{D6})$$

which we plot in Figure S8 and observe that our approximations are in agreement with simulations.

Appendix E Distribution of evolutionary rescue time

The probability that a successful mutant has been generated by time t is given by:

$$\begin{aligned} P(\text{rescue}, t) &= P(T_a < t) \\ &= 1 - \exp \left\{ - [r_1(t) + r_2(t)] \right\} \\ &= 1 - \exp \left\{ - \left[\frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a} \right) + v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s} \right] \right\}, \end{aligned}$$

where T_a is the time at which the first mutant cell appears that will avoid extinction and which was defined in appendix C.

As a result, the probability that a successful mutant has not been generated by time t is:

$$1 - P(\text{rescue}, t) = \exp \left\{ - \left[\frac{uv\lambda_s \lambda_a N p_m}{\Delta_s - \Delta_a} \left(\frac{e^{\Delta_s t} - 1}{\Delta_s} - \frac{e^{\Delta_a t} - 1}{\Delta_a} \right) + v\lambda_s N p_m \frac{e^{\Delta_s t} - 1}{\Delta_s} \right] \right\}. \quad (\text{E1})$$

Appendix F Distribution of recurrence time

The probability distribution of the time that a lineage, consisting initially of a single cell, will reach size N as time t is given by the Gumbel distribution $\text{Gumb}_{\max} \left(\frac{\log N p_m}{\Delta_m}, \frac{1}{\Delta_m} \right)$ (Avanzini and Antal, 2019) with probability density function:

$$G(t) = e^{-p_m N e^{-\Delta_m t}}.$$

A mutant lineage initiated at time s , through aneuploidy, at rate $v\lambda_a p_m a_s$ reaches size N before time t with probability $G(t - s)$ where $s \leq t$. As a result, the number of successful mutant lineages which reach size N by time t can be approximated by inhomogeneous Poisson random variable with rate:

$$r(t) = v\lambda_a p_m \int_0^t a_s G(t - s) ds$$

where a_s is aneuploid population size at time s defined in eq. (C4). The proliferation time is defined as the first time the size of all lineages reaches N . When $N \ll |\Delta_s||\Delta_a| / uv\lambda_s\lambda_ap_m$ there is at most a single mutant lineage that will survive and reach size N (Figure S3) and the probability that the size of that lineage has not reached N by time t is given by:

$$P(m_t \leq N) = \exp[-r(t)] \\ = \exp\left[-\frac{Nuv\lambda_s\lambda_ap_m}{\Delta_s - \Delta_a} \int_0^t \left[e^{\Delta_s x} - e^{\Delta_a x}\right] e^{-p_m N e^{-\Delta_m(t-x)}} dx\right]. \quad (F1)$$

When $N \gg |\Delta_s||\Delta_a| / uv\lambda_s\lambda_ap_m$ the dynamics of the cancer cell populations is deterministic and approximated by the system of ODEs shown in eq. (D2). As a result, the size of the mutant cell population will always be below N until time τ_a^r and will always be greater after:

$$P(m_t \leq N) = 1 - H(t - \tau_a^r), \quad (F2)$$

where $H(x)$ is the Heaviside function:

$$H(x) = \begin{cases} 0, & x < 0, \\ 1, & x \geq 0. \end{cases}$$

We plot eq. (F1) and eq. (F2) in Figure 6B and compare with stochastic simulations and observe that our approximations are in agreement.

We observe that for $N = 10^7$ our formula overestimates the probability that the mutant population will be smaller than N at time t . This can be explained by the fact that $N = 10^7$ is an intermediary scenario where the sensitive population produces a number of rescue lineages that is greater than one but still sufficiently small such that stochasticity plays an important role in the population dynamics. As a result, the number of mutant cancer cells will reach N faster than the scenario with a single mutant lineage. Additionally, we observe from Figure 6B that the probability of the mutant cell population reaching size N is approximately zero before time τ_a^r which is the recurrence time for the deterministic scenario. This can be explained as follows: in the deterministic scenario there is a sufficient number of lineages produced such that there exists a lineage where each descendant will only reproduce and not die; the time it takes for this lineage to reach N is the lower bound for the time of all other lineages to reach N and this time cannot be smaller than τ_a^r by definition. Given that for small values of N we expect that at most a single lineage will rescue the tumor, this lineage cannot reach N before τ_a^r for the deterministic scenario eq. (D4).

From eq. (F1) we obtain the distribution of the recurrence time conditional of evolutionary rescue:

$$f(t) = \frac{d}{dt} \left[\frac{P(m_t \geq N)}{p_{\text{rescue}}} \right] = r'(t) \frac{\exp[-r(t)]}{p_{\text{rescue}}}, \quad (F3)$$

which we plot in Figure S4 and compare with simulations. We note that in the scenario $N \gg |\Delta_s||\Delta_a| / uv\lambda_s\lambda_ap_m$ the distribution becomes the Dirac δ -function (Barton, 1989).

Appendix G Bootstrapping

For the mean times the 95% confidence interval is obtained through bootstrapping in the following steps: (1) we simulate T 100 times; (2) we sample with replacement which we store in T' ; (3) for each element of this sample we obtain $\tau = \mathbb{E}[T']$; (4) we repeat steps (2)-(3) 100 times to obtain τ and

we select the upper and lower limits such that 95% of the values of τ lie in the interval given by the bounds.

For the threshold tumor sizes the 95% confidence interval is obtained through bootstrapping in the following steps: (1) we simulate p_{rescue} 100 times; (2) we sample with replacement which we store in S ; (3) for each element of this sample we obtain $N_a^* = 1/p_s$ using $p_s = -1/N_e \log(1 - \bar{S})$ where \bar{S} is the mean of S and N_e is an arbitrary value of the initial population size we selected in order to calculate p_{rescue} ; (4) we repeat steps (2)-(3) 100 times to obtain N_a^* and we select the upper and lower limits such that 95% of the values of N_a^* lie in the interval given by the bounds.

For the ratio of the threshold tumor sizes the 95% confidence interval is obtained through bootstrapping in the following steps: (1) we simulate p_{rescue} 100 times for both the scenario when $f = \tilde{u}\lambda_s/c$ and $f = 0$; (2) we sample with replacement which we store in S_f and S_0 ; (4) for each element of S_0 we obtain $N_a^* = 1/p_s$ using $p_s = -1/N_e \log(1 - \bar{S})$ where \bar{S} is the mean of S_0 and N_e is an arbitrary value of the initial population size we selected in order to calculate p_{rescue} ; (5) for each element of S_f we obtain $\tilde{N}_a^* = 1/p_a$ using $p_a = -f/N_e \log(1 - \bar{S})$ where \bar{S}_f is the mean of S_f and N_e is an arbitrary value of the initial population size we selected in order to calculate p_{rescue} ; (6) we repeat steps (2)-(5) 100 times to obtain \tilde{N}_a^*/N_a^* and we select the upper and lower limits such that 95% of the values of \tilde{N}_a^*/N_a^* lie in the interval given by the bounds.

Appendix H Aneuploidy-induced mutation rate

The mutation rate may be increased in aneuploid cells. To account for an increased mutation rate in cells with the aneuploidy that provides a fitness advantage in the presence of a drug, we extend our model such that sensitive cells mutate with rate v_s and aneuploid cells mutate with rate v_a . Note that sensitive cells include those cells with any other aneuploidy, including those that may cause an increased mutation rate, and therefore those cases are already covered by the model presented in the main text. We then calculate the survival probabilities p_s , p_a and p_m as in Appendix A,

$$\begin{aligned}
1 - p_s &= \frac{\mu_s}{\lambda_s + \mu_s + u\lambda_s + v_s\lambda_s} + \frac{u\lambda_s}{\lambda_s + \mu_s + u\lambda_s + v_s\lambda_s} (1 - p_a) (1 - p_s) + \\
&\quad \frac{\lambda_s}{\lambda_s + \mu_s + u\lambda_s + v_s\lambda_s} (1 - p_s)^2 + \frac{v_s\lambda_s}{\lambda_s + \mu_s + u\lambda_s + v_s\lambda_s} (1 - p_m) (1 - p_s), \\
1 - p_a &= \frac{\mu_a}{\lambda_a + \mu_a + v_a\lambda_a} + \frac{v_a\lambda_a}{\lambda_a + \mu_a + v_a\lambda_a} (1 - p_m) (1 - p_a) + \frac{\lambda_a}{\lambda_a + \mu_a + v_a\lambda_a} (1 - p_a)^2, \\
1 - p_m &= \frac{\mu_m}{\lambda_m + \mu_m} + \frac{\lambda_m}{\lambda_m + \mu_m} (1 - p_m)^2.
\end{aligned} \tag{H1}$$

Solving the above equations we obtain

$$\begin{aligned}
p_s &= \frac{\lambda_s - \mu_s - u\lambda_s p_a - v_s\lambda_s p_m + \sqrt{(\lambda_s - \mu_s - u\lambda_s p_a - v_s\lambda_s p_m)^2 + 4\lambda_s^2 (u p_a + v_s p_m)}}{2\lambda_s}, \\
p_a &= \frac{\lambda_a - \mu_a - v_a\lambda_a p_m + \sqrt{(\lambda_a - \mu_a - v_a\lambda_a p_m)^2 + 4\lambda_a^2 v_a p_m}}{2\lambda_a}, \\
p_m &= \frac{\lambda_m - \mu_m}{\lambda_m}.
\end{aligned} \tag{H2}$$

Consequently, the threshold population size can be written as

$$N_a^* \approx \frac{|\Delta_s|}{u\lambda_s} \cdot \begin{cases} \frac{|\Delta_a|}{v_a\lambda_a} \frac{\lambda_m}{\Delta_m}, & \Delta_a T^* \ll -1 \text{ (tolerant aneuploids),} \\ 2\lambda_a T^*, & -1 \ll \Delta_a T^* \ll 1 \text{ (stationary aneuploids),} \\ \frac{\lambda_a}{\Delta_a}, & \Delta_a T^* \gg 1 \text{ (resistant aneuploids),} \end{cases} \quad (\text{H3})$$

where $T^* = \left(4v_a\lambda_a^2 p_m\right)^{-\frac{1}{2}}$. This is the same as in eq. (3) except with v_a instead of v .

The probability of evolutionary rescue is

$$p_{\text{rescue}} = 1 - (1 - p_s)^N \approx 1 - e^{-Np_s} = 1 - e^{-N/N_a^*}, \quad (\text{H4})$$

which we plot in Figure S10 for multiple values of v_a . We note that when $v_a = 10^{-5}$, we are in the case of stationary aneuploidy (i.e., $\Delta_a T^* \approx -0.55$).

Supplementary Figures

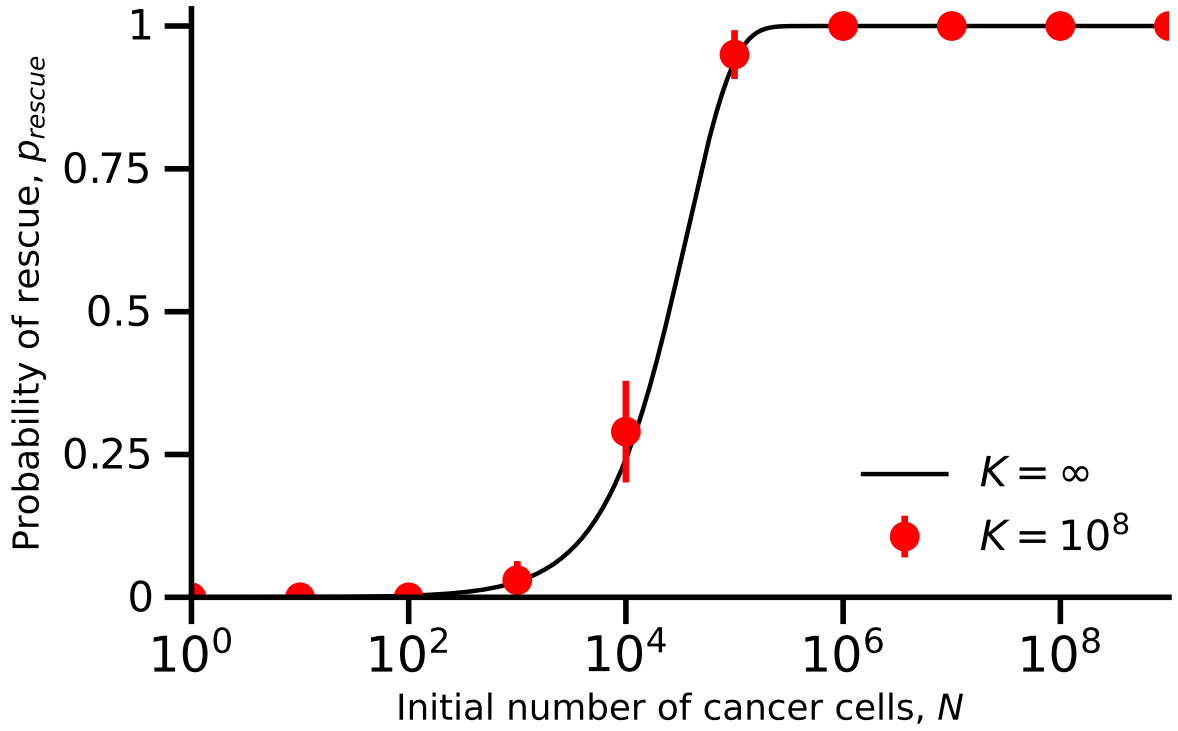


Figure S1: Density dependent growth does not affect the accuracy of our model. Comparison of results of simulations with density-dependent growth (red markers with with 95% CI) and the approximation formula (black line, eq. (3) in eq. (1)) with maximum carrying capacity $K = 10^8$ and effective carrying capacity $K_e = K\Delta_a/\lambda_a \approx 10^6$. The error bars represent 95% confidence interval of the form $p \pm 1.96\sqrt{p(1-p)/n}$ where p is the fraction of simulations in which the tumor has adapted to the stress and $n = 100$ is the number of simulations. Parameters: $\lambda_s = 0.1, \lambda_a = 0.0901, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}, K = 10^8$.

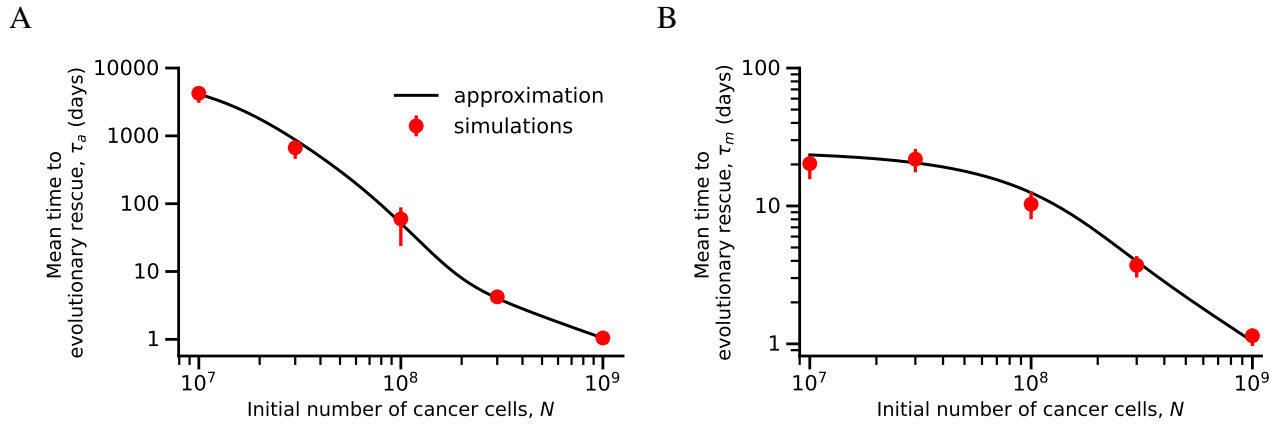


Figure S2: Evolutionary rescue time. Shown is the mean time for appearance of a resistance mutation that leads to evolutionary rescue (A) with aneuploidy ($u > 0$) and (B) without aneuploidy ($u = 0$). Our inhomogeneous Poisson-process approximations (solid black lines, right: eq. (C2), left: eq. (C7)) are in agreement with simulation results (red markers with 95% quantile intervals obtained with bootstrapping, see Appendix G). Parameters: $\lambda_s = 0.1$, $\lambda_a = 0.0899$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $u = 10^{-2}$, $v = 10^{-7}$.

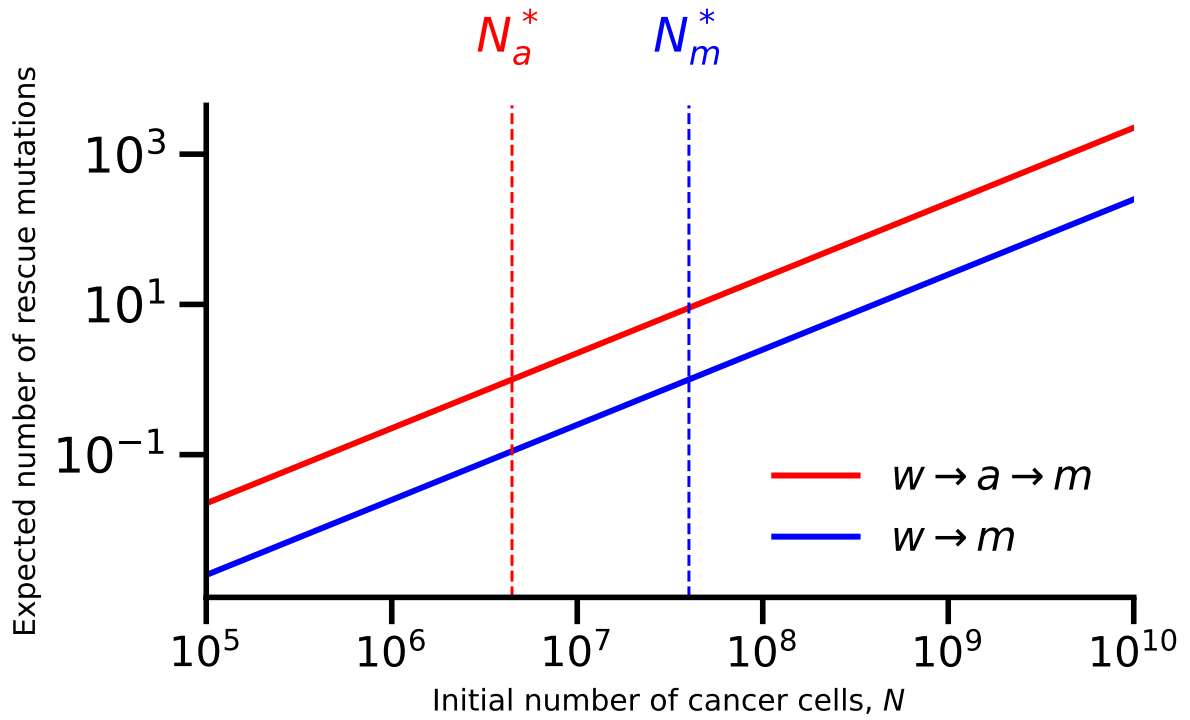


Figure S3: Aneuploidy increases the number of mutations which rescue the tumor. Shown is the expected number of mutations, which will rescue the cancer cell population, produced through the evolutionary trajectory *sensitive* \rightarrow *mutant* (blue line, eq. (C6)) or through the trajectory *sensitive* \rightarrow *aneuploid* \rightarrow *mutant* (red line, eq. (C5)). Dashed vertical red line represents the threshold tumor size above which evolutionary rescue is very likely through aneuploidy eq. (3) and the dashed vertical blue line represents the threshold tumor size above which evolutionary rescue is very likely through direct mutation eq. (2). Parameters: $\lambda_s = 0.1$, $\lambda_a = 0.0899$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $u = 10^{-2}$, $v = 10^{-7}$.

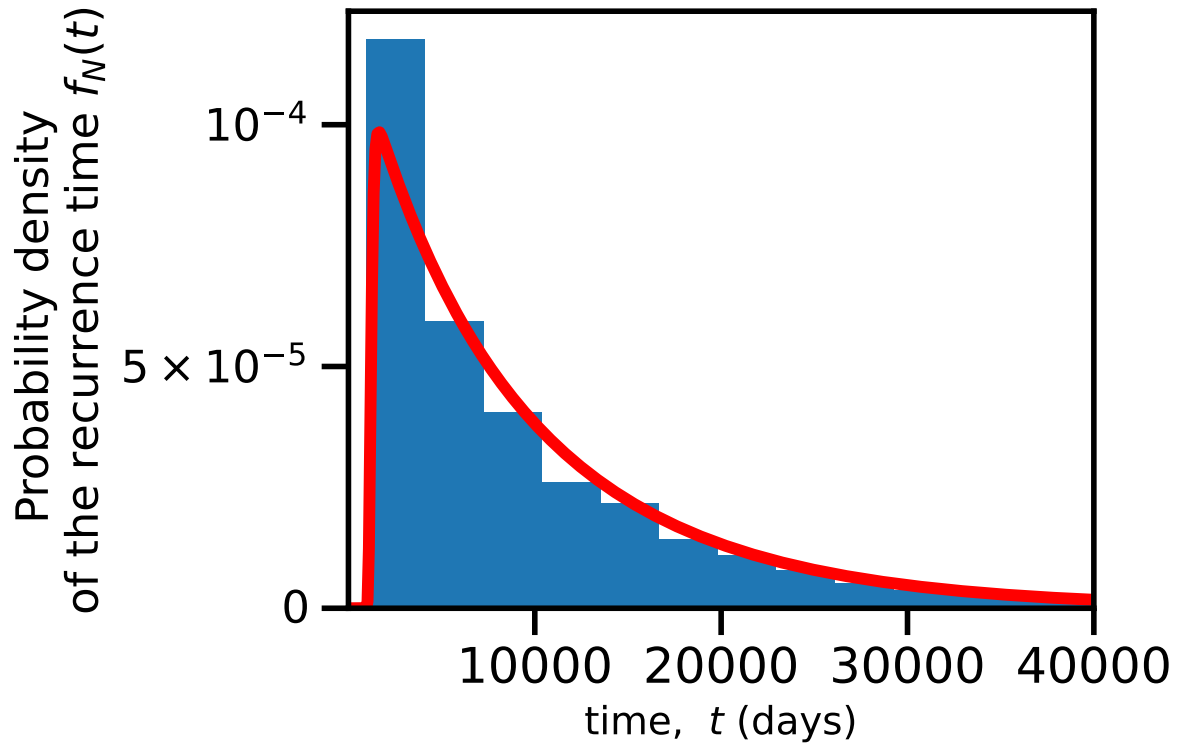


Figure S4: Distribution of the recurrence time. Shown is the distribution of the time for the mutant cell population to reach size N , where N is the initial number of cancer cells. The red line is analytic result eq. (F3) overlaid over the histogram of simulations. Parameters: $N = 10^6$, $\lambda_s = 0.1$, $\lambda_a = 0.0899$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $u = 10^{-2}$, $v = 10^{-7}$.

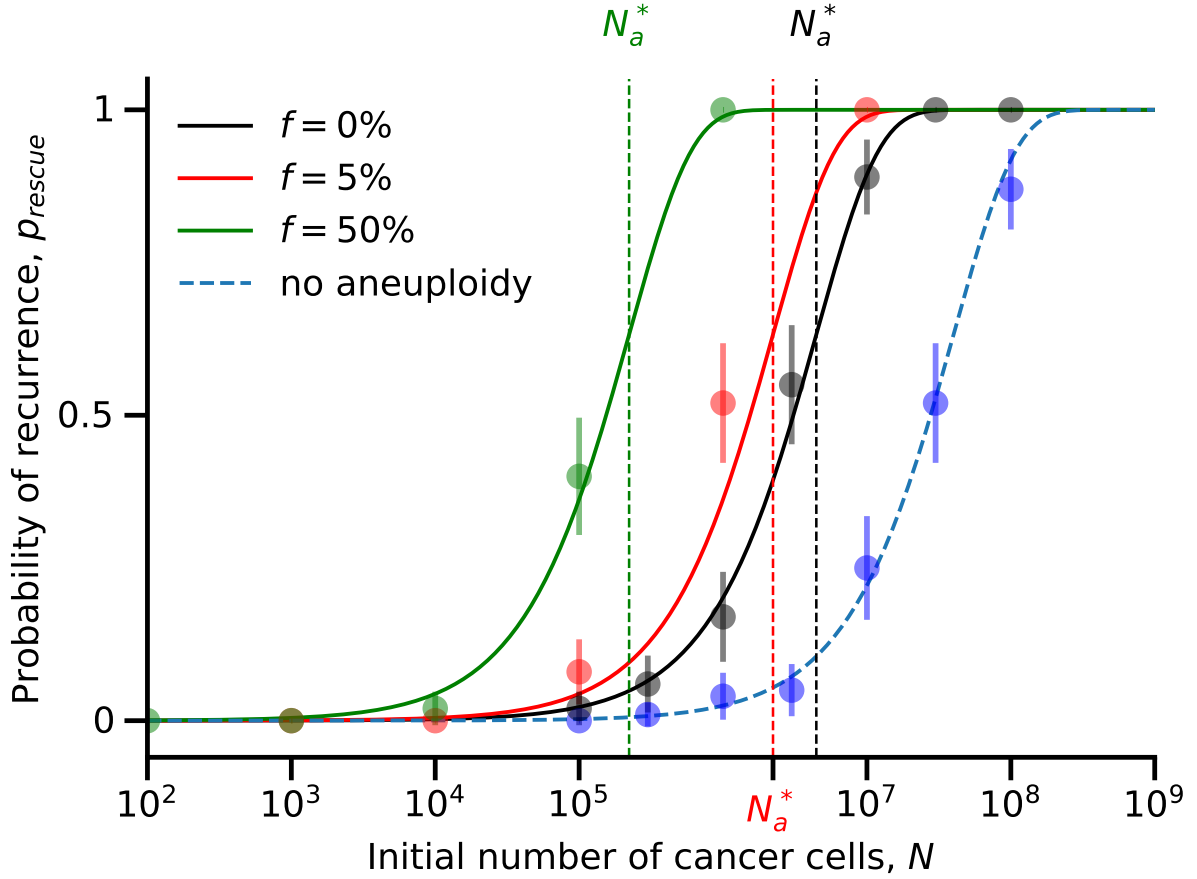


Figure S5: The probability of evolutionary rescue (i.e., the probability that the population does not go to extinction), p_{rescue} , as a function of the initial tumor size, N . Dashed vertical line shows the threshold tumor size, above which the probability is very high. Blue dashed line represents the probability of evolutionary rescue as a function of N without aneuploidy ($u = 0$). The black line represents the scenario where a fraction $f = 0\%$ of the initial tumor is aneuploid, the red line represents the scenario with $f = 5\%$ and the green line represents the scenario with $f = 50\%$. The dots represent simulation results and the error bars represent 95% confidence intervals ($p \pm 1.96\sqrt{p(1-p)/n}$ where p is the fraction of simulations in which the tumor has adapted to the stress and $n = 100$ is the number of simulations). Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}$.

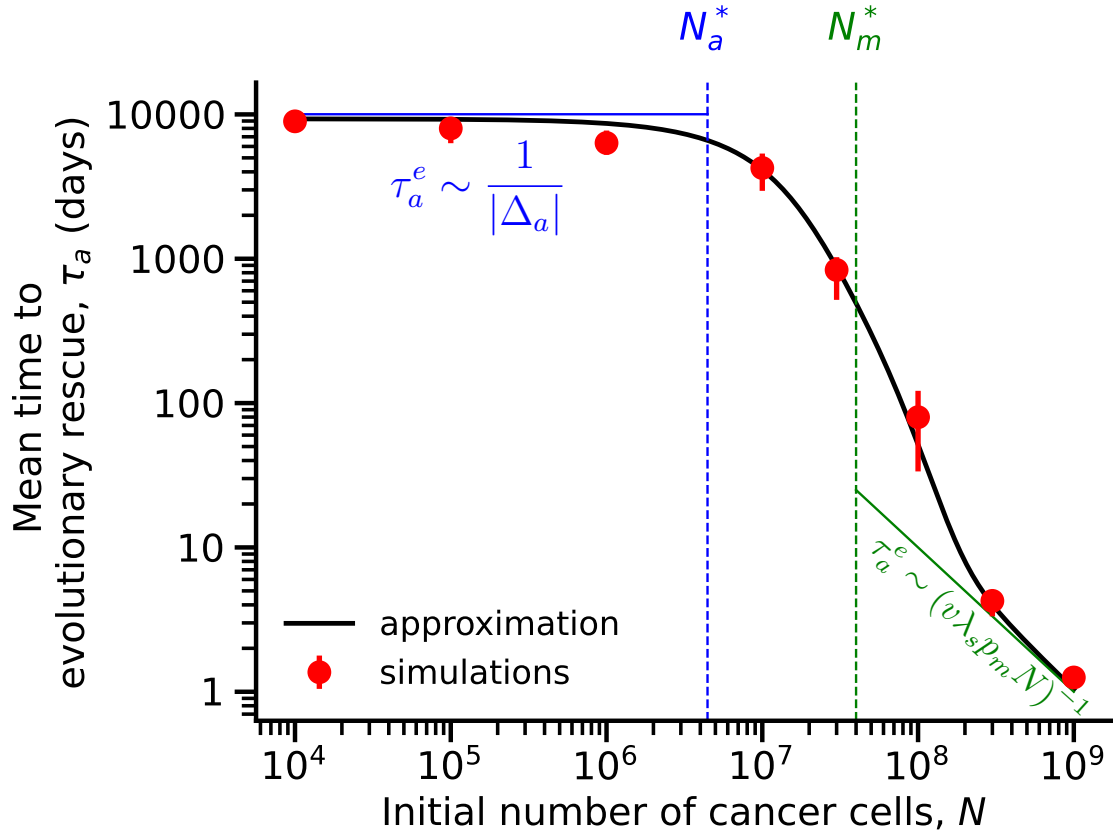


Figure S6: Shown is the mean time for appearance of a resistance mutation that leads to evolutionary rescue with aneuploidy ($u > 0$). Our inhomogeneous Poisson-process approximations (solid black lines: eq. (C7)) are in agreement with simulation results (red markers with 95% confidence intervals obtained with bootstrapping, see Appendix G). Dashed vertical blue line represents the threshold tumor size above which evolutionary rescue is very likely through aneuploidy eq. (3) and the dashed vertical green line represents the threshold tumor size above which evolutionary rescue is very likely through direct mutation eq. (2). Solid lines represent the approximations eq. (7) ($N < N_a^*$ blue line and $N > N_m^*$ green line). Parameters: $\lambda_s = 0.1$, $\lambda_m = 0.0899$, $\lambda_a = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $u = 10^{-2}$, $v = 10^{-7}$.

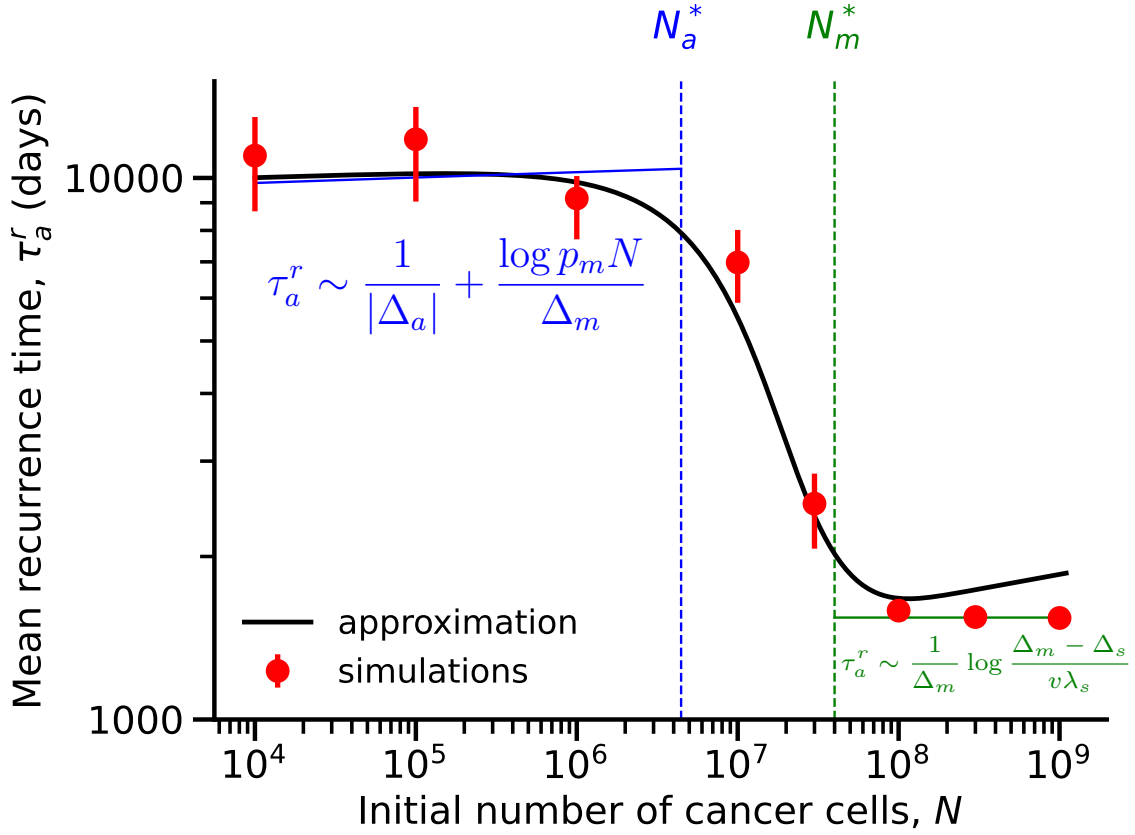


Figure S7: The mean time for the mutant cell population to reach size N , where N is the initial number of cancer cells. Our inhomogeneous Poisson-process approximation (solid black line, eq. (D1)) is in agreement with simulation results (red markers with 95% confidence intervals obtained with bootstrapping, see Appendix G) for small and intermediate values of N . Dashed vertical blue line represents the threshold tumor size above which evolutionary rescue is very likely through aneuploidy eq. (3) and the dashed vertical green line represents the threshold tumor size above which evolutionary rescue is very likely through direct mutation eq. (2). Solid lines represents the approximations eq. (8) ($N < N_a^*$ blue line and $N > N_m^*$ green line). The simulations converge to eq. (D4) (green line) for large values of $N \gg N_m^*$. Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}$.

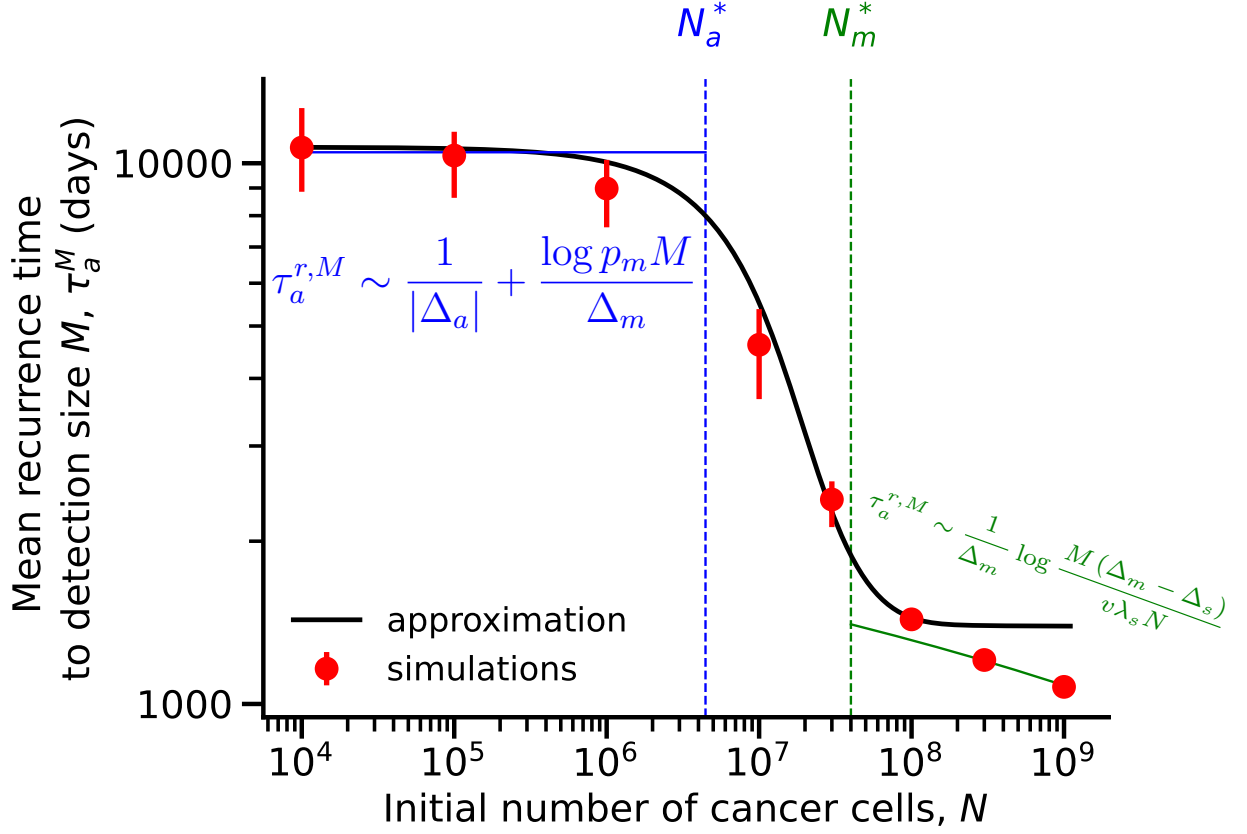


Figure S8: The mean time for the mutant cell population to reach size M , where M is the tumor detection size. Our inhomogeneous Poisson-process approximation (solid black line, eq. (D5)) is in agreement with simulation results (red markers with 95% confidence intervals obtained with bootstrapping, see Appendix G) for small and intermediate values of N . Dashed vertical blue line represents the threshold tumor size above which evolutionary rescue is very likely through aneuploidy eq. (3) and the dashed vertical green line represents the threshold tumor size above which evolutionary rescue is very likely through direct mutation eq. (2). Solid blue line represents the approximation eq. (D5) with τ_a from eq. (7) for $N < N_a^*$ and the solid green line represents the approximation eq. (D6) for $N > N_m^*$. The simulations converge to eq. (D6) (green line) for large values of $N \gg N_m^*$. Parameters: $\lambda_s = 0.1, \lambda_a = 0.0899, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v = 10^{-7}, M = 10^7$.

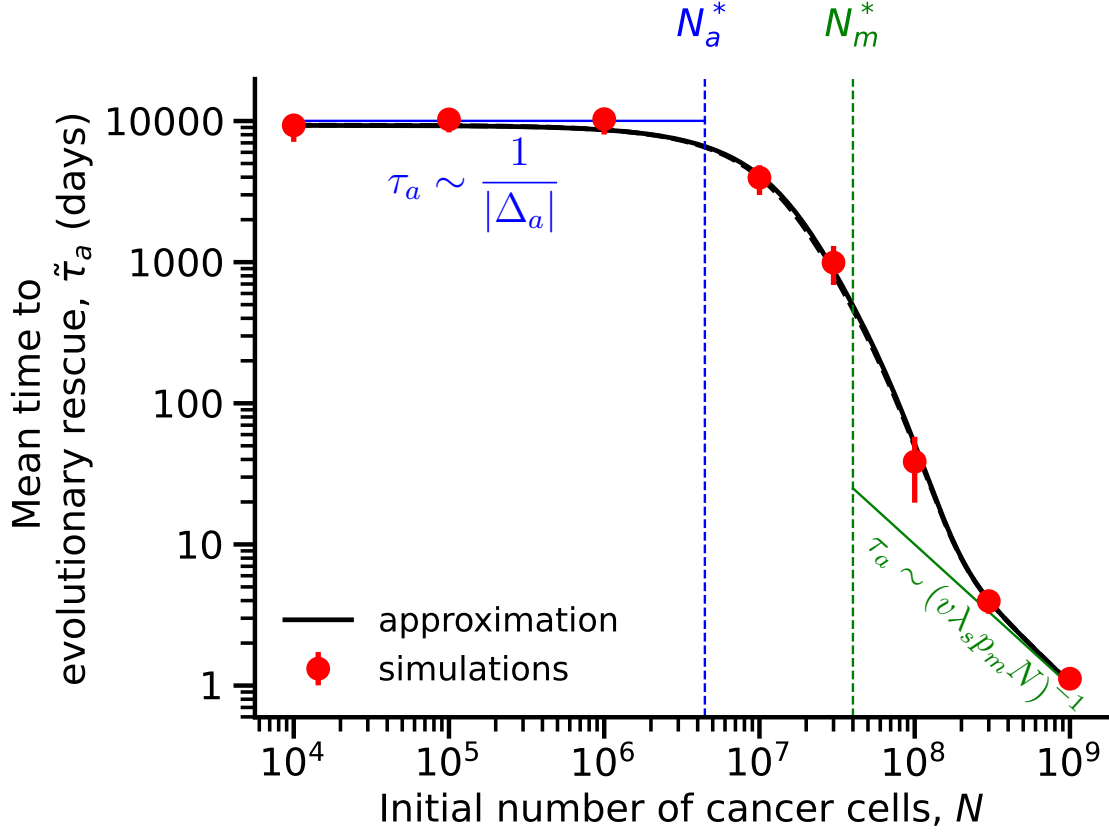


Figure S9: Shown is the mean time for appearance of a resistance mutation that leads to evolutionary rescue with aneuploidy ($u > 0$) when a fraction f of cancer cells are aneuploid at the start of therapy. Black lines represent our inhomogeneous Poisson-process approximations (solid black line, eq. (C7); dashed black line eq. (C10)). Dashed black line is the inhomogeneous Poisson-process approximation where a fraction f of tumor is aneuploid at the onset of drug therapy which is in agreement with simulation results (red markers with 95% confidence intervals obtained with bootstrapping, see Appendix G). Dashed vertical blue line represents the threshold tumor size above which evolutionary rescue is very likely through aneuploidy eq. (3) and the dashed vertical green line represents the threshold tumor size above which evolutionary rescue is very likely through direct mutation eq. (2). Solid lines represents the approximations eq. (7) ($N < N_a^*$ blue line and $N > N_m^*$ green line). Parameters: $\lambda_s = 0.1$, $\lambda_a = 0.0899$, $\lambda_m = 0.1$, $\mu_s = 0.14$, $\mu_a = 0.09$, $\mu_m = 0.09$, $u = 10^{-2}$, $v = 10^{-7}$, $f = 0.14\%$.

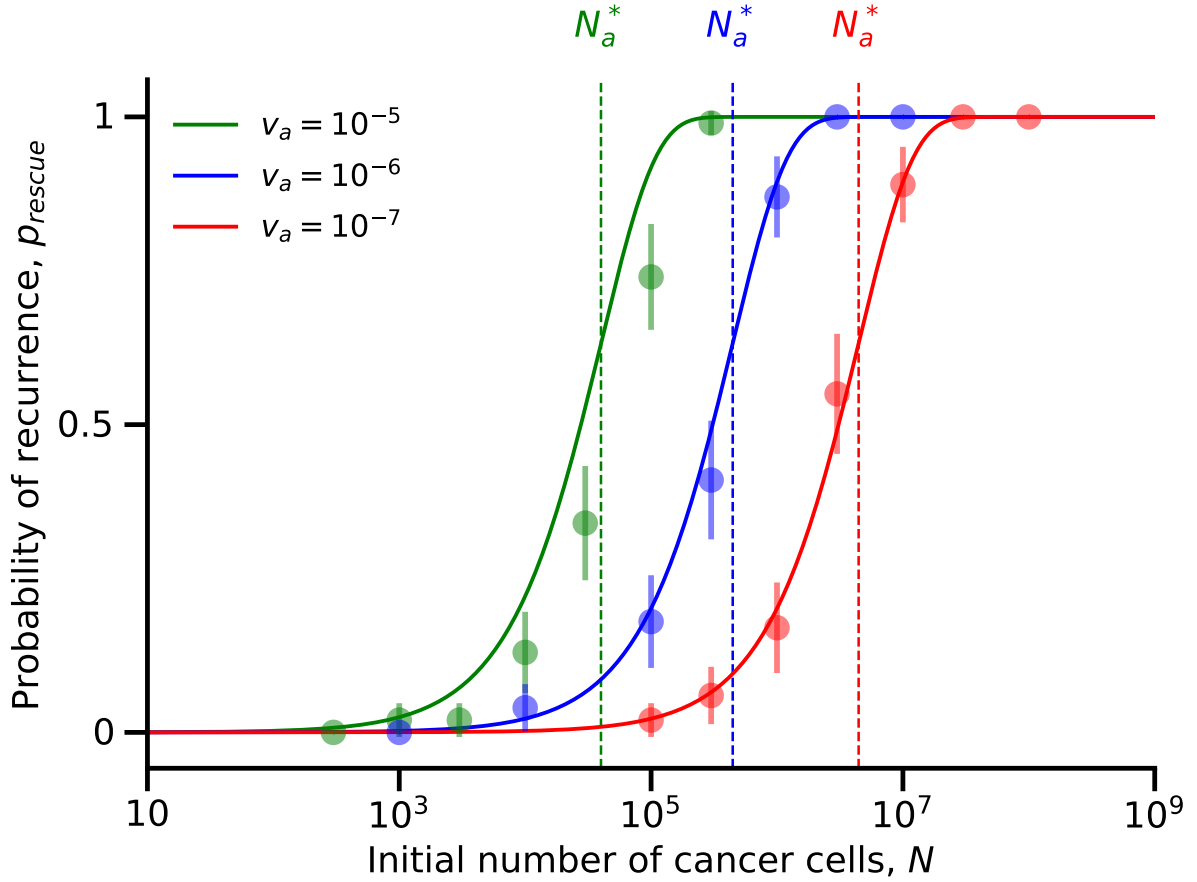


Figure S10: The probability of evolutionary rescue (i.e., the probability that the population does not become extinct), p_{rescue} , as a function of the initial tumor size, N (eq. (1)). Dashed vertical line shows the threshold tumor size, N_a^* , above which the probability is very high (eq. (H3)). Red dashed line: $v_a = 10^{-7}$. blue line: $v_a = 10^{-6}$. Green line: $v_a = 10^{-5}$. Dots for simulations and the error bars for 95% confidence interval ($p \pm 1.96\sqrt{p(1-p)/n}$ where p is the fraction of simulations in which the tumor has been rescued and $n = 100$ is the number of simulations). Parameters: $\lambda_s = 0.1, \lambda_m = 0.1, \mu_s = 0.14, \mu_a = 0.09, \mu_m = 0.09, u = 10^{-2}, v_s = 10^{-7}$.