

RESEARCH ARTICLE

# Likelihood Ratio Test for Excess Homozygosity at Marker Loci on X Chromosome

Xiao-Ping You, Qi-Lei Zou, Jian-Long Li, Ji-Yuan Zhou\*

State Key Laboratory of Organ Failure Research and Guangdong Provincial Key Laboratory of Tropical Research, School of Public Health and Tropical Medicine, Southern Medical University, Guangzhou, Guangdong, China

\* [zhoujiyuan5460@hotmail.com](mailto:zhoujiyuan5460@hotmail.com)



OPEN ACCESS

**Citation:** You X-P, Zou Q-L, Li J-L, Zhou J-Y (2015) Likelihood Ratio Test for Excess Homozygosity at Marker Loci on X Chromosome. PLoS ONE 10(12): e0145032. doi:10.1371/journal.pone.0145032

**Editor:** Dmitri Zaykin, NIH - National Institute of Environmental Health Sciences, UNITED STATES

**Received:** March 11, 2015

**Accepted:** November 28, 2015

**Published:** December 15, 2015

**Copyright:** © 2015 You et al. This is an open access article distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

**Data Availability Statement:** All relevant data are within the paper and its Supporting Information files. The rheumatoid arthritis data are from North American Rheumatoid Arthritis Consortium, which are available from Genetic Analysis Workshop 15.

**Funding:** This work was supported by the National Natural Science Foundation of China (81373098), Science and Technology Planning Project of Guangdong Province, China (2013B021800038) to Professor Ji-Yuan Zhou. The Genetic Analysis Workshops are supported by the National Institutes of Health grant R01 GM031575. The RA data were gathered with the support of grants from the National Institutes of Health (NO1-AR-2-2263 and R01-AR-

## Abstract

The assumption of Hardy-Weinberg equilibrium (HWE) is generally required for association analysis using case-control design on autosomes; otherwise, the size may be inflated. There has been an increasing interest of exploring the association between diseases and markers on X chromosome and the effect of the departure from HWE on association analysis on X chromosome. Note that there are two hypotheses of interest regarding the X chromosome: (i) the frequencies of the same allele at a locus in males and females are equal and (ii) the inbreeding coefficient in females is zero (without excess homozygosity). Thus, excess homozygosity and significantly different minor allele frequencies between males and females are used to filter X-linked variants. There are two existing methods to test for (i) and (ii), respectively. However, their size and powers have not been studied yet. Further, there is no existing method to simultaneously detect both hypotheses till now. Therefore, in this article, we propose a novel likelihood ratio test for both (i) and (ii) on X chromosome. To further investigate the underlying reason why the null hypothesis is statistically rejected, we also develop two likelihood ratio tests for detecting (i) and (ii), respectively. Moreover, we explore the effect of population stratification on the proposed tests. From our simulation study, the size of the test for (i) is close to the nominal significance level. However, the size of the excess homozygosity test and the test for both (i) and (ii) is conservative. So, we propose parametric bootstrap techniques to evaluate their validity and performance. Simulation results show that the proposed methods with bootstrap techniques control the size well under the respective null hypothesis. Power comparison demonstrates that the methods with bootstrap techniques are more powerful than those without bootstrap procedure and the existing methods. The application of the proposed methods to a rheumatoid arthritis dataset indicates their utility.

44422), and the National Arthritis Foundation. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

**Competing Interests:** The authors have declared that no competing interests exist.

## Introduction

Association analysis is a useful tool to map disease loci by using markers on autosomes based on family data and case-control data [1–9]. There has been an increasing interest of exploring the association between diseases and markers on X chromosome and the effect of the departure from Hardy-Weinberg equilibrium (HWE) on association analysis on X chromosome [10–17]. Note that there are two hypotheses of interest regarding the X chromosome: (i) the frequencies of the same allele at a locus in males and females are equal and (ii) the inbreeding coefficient in females is zero (without excess homozygosity) in X-specific quality control [18, 19]. As such, excess homozygosity in females and significantly different minor allele frequencies between males and females are used to filter X-linked variants [20, 21]. The inbreeding coefficient is generally estimated by functions of excess homozygosity [22, 23], which may be caused by population substructure, consanguineous mating or factors like null alleles [24, 25]. Overall and Nichols developed an approach to distinguish population substructure and consanguinity by using multilocus genotype data [24]. On the other hand, Zheng et al. proposed two test statistics to test for the equality of the frequencies of the same allele in males and females and the zero inbreeding coefficient in females on X chromosome, respectively [14]. However, they only focused on association analysis on X chromosome and the type I error rates and powers of these two test statistics have not been studied yet. Further, there is no existing method to simultaneously detect both of the issues till now.

Therefore, in this article, we first combine two test statistics proposed in zheng et al. [14] and suggest  $Z_0$  to simultaneously test for (i) the equality of the frequencies of the same allele in males and females and (ii) the zero inbreeding coefficient on X chromosome based on the collected sample. For the purpose of improving the test power for both (i) and (ii), a novel likelihood ratio test on X chromosome is proposed. We write out the likelihood functions of the collected sample under the null hypothesis and alternative hypothesis at a single locus on X chromosome, respectively. Next, we obtain the maximum likelihood estimates (MLEs) of the unknown parameters by expectation-maximization (EM) algorithms [26] and construct the corresponding likelihood ratio test ( $LRT_0$ ) statistic to test for both (i) and (ii). If the null hypothesis is statistically rejected, we further conduct two hypothesis testing issues to find the underlying reasons why the null hypothesis is violated by proposing another two likelihood ratio tests  $LRT_1$  (for the equality of the frequencies of the same allele in males and females) and  $LRT_2$  (for excess homozygosity). Note that the size of  $LRT_0$  and  $LRT_2$  is conservative from our simulation study. As such, we use parametric bootstrap techniques to evaluate the validity and performance of  $LRT_0$  and  $LRT_2$ , which are respectively denoted by  $LRT_{0b}$  and  $LRT_{2b}$ . Moreover, we explore the effect of population stratification on the proposed tests. In addition, the root mean squared error (RMSE) and bias are used to assess the accuracy of the MLEs of the unknown parameters. Finally, the application of the proposed methods to a rheumatoid arthritis (RA) dataset indicates their utility.

## Materials and Methods

### Background and notations

Consider a biallelic marker locus on X chromosome with alleles  $M_1$  and  $M_2$ . Let  $p_m$  and  $p_f$  be the frequencies of  $M_1$  in males and females, respectively. As such, the frequencies of  $M_2$  in males and females are  $q_m = 1 - p_m$  and  $q_f = 1 - p_f$ , respectively. In females, let  $\rho$  be the inbreeding coefficient, which is generally nonnegative [27–29]. Thus, the frequencies of three genotypes  $M_1M_1$ ,  $M_1M_2$  and  $M_2M_2$  in females can be expressed as follows:

$$P(M_1M_1) = p_f^2 + \rho p_f q_f, P(M_1M_2) = 2(1 - \rho) p_f q_f, P(M_2M_2) = q_f^2 + \rho p_f q_f.$$

To this end, there is no excess homozygosity in females when  $\rho = 0$ ; excess homozygosity exists when  $\rho > 0$ . Note that  $p_m \neq p_f$  may be true on X chromosome. So, we construct the null hypothesis denoted by  $H_0: p_m = p_f$  and  $\rho = 0$  to test for both of the hypotheses (i) and (ii). If the null hypothesis is violated, we need to investigate which one of  $p_m \neq p_f$  and  $\rho > 0$  is true. As such, we have other two hypothesis testing issues with the null hypothesis being  $H_{01}: p_m = p_f$  and  $H_{02}: \rho = 0$ , respectively. It should be noted that X chromosome has the problem of X chromosome inactivation and dosage compensation [30], but we do not consider them in this section. The corresponding discussion can be found later (see the Discussion section).

Assume that  $n_{1m}$  and  $n_{0m}$  represent the numbers of males with alleles  $M_1$  and  $M_2$  in a collected sample, respectively;  $n_{2f}$ ,  $n_{1f}$  and  $n_{0f}$  denote the numbers of females with genotypes  $M_1M_1$ ,  $M_1M_2$  and  $M_2M_2$ , respectively. Then,  $N_m = n_{1m} + n_{0m}$  and  $N_f = n_{2f} + n_{1f} + n_{0f}$  are respectively the numbers of males and females in the sample, and  $N = N_m + N_f$  is the sample size.

### Existing methods $Z_1$ and $Z_2$ for $H_{01}$ (equality of the frequencies of the same allele in males and females) and $H_{02}$ (zero inbreeding coefficient), respectively

Zheng et al. [14] proposed the test statistic

$$Z_1 = \frac{(\hat{p}_m - \hat{p}_f)^2}{\text{Var}(\hat{p}_m) + \text{Var}(\hat{p}_f)}$$

to test for  $H_{01}: p_m = p_f$  where  $\hat{p}_m = n_{1m}/N_m$  and  $\hat{p}_f = (2n_{2f} + n_{1f})/(2N_f)$  are the estimates of  $p_m$  and  $p_f$ ,  $\text{Var}(\hat{p}_m) = \hat{p}_m(1 - \hat{p}_m)/N_m$ , and  $\text{Var}(\hat{p}_f) = [\hat{p}_f - 2\hat{p}_f^2 + \hat{P}(M_1M_1)]/(2N_f)$  are the estimates of the variances of  $\hat{p}_m$  and  $\hat{p}_f$  under  $H_{01}$ , respectively, with  $\hat{P}(M_1M_1) = n_{2f}/N_f$ . Under  $H_{01}$ ,  $Z_1$  asymptotically follows the chi-square distribution with one degree of freedom when the sample size is large enough.

Weir and cockerham [31] introduced the disequilibrium coefficient in females  $\Delta_f = P(M_1M_1) - p_f^2 = \rho p_f q_f$ . In other words, testing for  $\Delta_f = 0$  is equivalent to testing for  $\rho = 0$ . Hence, zheng et al. [14] further developed the following test statistic to test for  $H_{02}: \rho = 0$ ,

$$Z_2 = \frac{[\hat{\Delta}_f + \hat{p}_f \hat{q}_f / (2N_f)]^2}{\text{Var}(\hat{\Delta}_f)} = N_f \frac{[\hat{\Delta}_f + \hat{p}_f \hat{q}_f / (2N_f)]^2}{\hat{p}_f^2 \hat{q}_f^2},$$

where  $\hat{\Delta}_f = \hat{P}(M_1M_1) - \hat{p}_f^2$ ,  $\hat{q}_f = 1 - \hat{p}_f$ ,  $E(\hat{\Delta}_f) = -p_f q_f / (2N_f)$  and  $\text{Var}(\hat{\Delta}_f) = p_f^2 q_f^2 / N_f$ . Under  $H_{02}$ ,  $Z_2$  approximately follows the chi-square distribution with one degree of freedom when  $N_f$  is large enough. It should be noted that the test  $Z_2$  has nothing to do with male individuals and thus only needs female individuals.

### $Z_0$ test for both hypotheses (i) and (ii) of interest regarding the X chromosome

Zheng et al. [14] showed that, under  $H_0: p_m = p_f$  and  $\rho = 0$ ,  $Z_1$  and  $Z_2$  are independent. However, they did not propose the corresponding test statistic for  $H_0$ . As such, we suggest the test statistic

$$Z_0 = Z_1 + Z_2$$

to test for  $H_0: p_m = p_f$  and  $\rho = 0$ . Under  $H_0$ ,  $Z_0$  asymptotically follows the chi-square distribution

with the degrees of freedom being 2. Moreover, it should be noted that we can use

$$\hat{\rho}_z = \frac{\hat{P}(M_1M_1) - \hat{p}_f^2}{\hat{p}_f\hat{q}_f}$$

to estimate the inbreeding coefficient  $\rho$ .

### Likelihood ratio test for both hypotheses (i) and (ii) of interest regarding the X chromosome

To construct a likelihood ratio test (LRT) for  $H_0: p_m = p_f$  and  $\rho = 0$ , we give the likelihood function of the sample as follows:

$$L(\theta) = \binom{N_m}{n_{1m}} \binom{N_f}{n_{2f}, n_{1f}, n_{0f}} p_m^{n_{1m}} q_m^{n_{0m}} (p_f^2 + \rho p_f q_f)^{n_{2f}} \times [2(1 - \rho)p_f q_f]^{n_{1f}} (q_f^2 + \rho p_f q_f)^{n_{0f}}, \tag{1}$$

where  $\theta = (p_m, p_f, \rho)$ . Firstly, we use the following EM algorithm to estimate the unknown parameters  $p_m, p_f$  and  $\rho$  under the alternative hypothesis ( $H_1: p_m \neq p_f$  or  $\rho > 0$ ). Suppose that  $Y = (Y_1, Y_2, Y_3, Y_4, Y_5) = (n_{1m}, n_{0m}, n_{2f}, n_{1f}, n_{0f})$  denotes the observed data.  $(Y_1, Y_2, Y_3, Y_4, Y_5)$  can be augmented by splitting the third cell into two cells  $W_1$  and  $W_2$ , which are unobservable random variables such that  $Y_3 = W_1 + W_2$  for female homozygote  $M_1M_1$  and  $W_1$  and  $W_2$  follow the binomial distributions with success probabilities  $p_f^2 / (p_f^2 + \rho p_f q_f)$  and  $\rho p_f q_f / (p_f^2 + \rho p_f q_f)$ , respectively, and by splitting the fifth cell into two cells  $W_3$  and  $W_4$ , where  $Y_5 = W_3 + W_4$  for female homozygote  $M_2M_2$  and  $W_3$  and  $W_4$  follow the binomial distributions with success probabilities  $q_f^2 / (q_f^2 + \rho p_f q_f)$  and  $\rho p_f q_f / (q_f^2 + \rho p_f q_f)$ , respectively. Thus, the likelihood function of complete data  $(n_{1m}, n_{0m}, w_1, w_2, n_{1f}, w_3, w_4)$  is:

$$L_c(\theta) \propto p_m^{n_{1m}} q_m^{n_{0m}} p_f^{2w_1 + w_2 + n_{1f} + w_4} q_f^{w_2 + n_{1f} + 2w_3 + w_4} \rho^{w_2 + w_4} (1 - \rho)^{n_{1f}},$$

where the normalizing constant is omitted for brevity.

At the E-step, the Q function at iteration  $(k + 1)$  is constructed as

$$Q(\theta|\theta^{(k)}) = n_{1m} \ln p_m + n_{0m} \ln q_m + [2E_{\theta^{(k)}}(w_1|n_{2f}) + E_{\theta^{(k)}}(w_2|n_{2f}) + n_{1f} + E_{\theta^{(k)}}(w_4|n_{0f})] \ln p_f + [E_{\theta^{(k)}}(w_2|n_{2f}) + n_{1f} + 2E_{\theta^{(k)}}(w_3|n_{0f}) + E_{\theta^{(k)}}(w_4|n_{0f})] \ln(1 - p_f) + [E_{\theta^{(k)}}(w_2|n_{2f}) + E_{\theta^{(k)}}(w_4|n_{0f})] \ln \rho + n_{1f} \ln(1 - \rho),$$

where  $\theta^{(k)}$  is the estimate of  $\theta$  at iteration  $k$ .

At the M-step, the estimated value  $\theta^{(k+1)}$  of  $\theta$  at iteration  $(k + 1)$  can be obtained by maximizing the Q function with respect to  $\theta$ . Therefore, the MLEs of  $p_m, p_f$  and  $\rho$  at iteration  $(k + 1)$

are respectively

$$\begin{aligned} \hat{p}_m &= \frac{n_{1m}}{N_m}, \\ \hat{p}_{f1}^{(k+1)} &= \frac{E_{\theta^{(k)}}(2w_1 + w_2|n_{2f}) + n_{1f} + E_{\theta^{(k)}}(w_4|n_{0f})}{2N_f}, \\ \hat{\rho}_1^{(k+1)} &= \frac{E_{\theta^{(k)}}(w_2|n_{2f}) + E_{\theta^{(k)}}(w_4|n_{0f})}{E_{\theta^{(k)}}(w_2|n_{2f}) + E_{\theta^{(k)}}(w_4|n_{0f}) + n_{1f}}. \end{aligned}$$

Note that the MLE of  $p_m$  is the same for all the iterations, which is also the same as zheng et al. [14]. In the above expressions,

$$E_{\theta^{(k)}}(w_1|n_{2f}) = \frac{n_{2f}(\hat{p}_{f1}^{(k)})^2}{(\hat{p}_{f1}^{(k)})^2 + \hat{\rho}_1^{(k)}\hat{p}_{f1}^{(k)}\hat{q}_{f1}^{(k)}}, \tag{2}$$

$$E_{\theta^{(k)}}(w_2|n_{2f}) = \frac{n_{2f}\hat{\rho}_1^{(k)}\hat{p}_{f1}^{(k)}\hat{q}_{f1}^{(k)}}{(\hat{p}_{f1}^{(k)})^2 + \hat{\rho}_1^{(k)}\hat{p}_{f1}^{(k)}\hat{q}_{f1}^{(k)}}, \tag{3}$$

$$E_{\theta^{(k)}}(w_3|n_{0f}) = \frac{n_{0f}(\hat{q}_{f1}^{(k)})^2}{(\hat{q}_{f1}^{(k)})^2 + \hat{\rho}_1^{(k)}\hat{p}_{f1}^{(k)}\hat{q}_{f1}^{(k)}}, \tag{4}$$

$$E_{\theta^{(k)}}(w_4|n_{0f}) = \frac{n_{0f}\hat{\rho}_1^{(k)}\hat{p}_{f1}^{(k)}\hat{q}_{f1}^{(k)}}{(\hat{q}_{f1}^{(k)})^2 + \hat{\rho}_1^{(k)}\hat{p}_{f1}^{(k)}\hat{q}_{f1}^{(k)}}, \tag{5}$$

where  $\hat{q}_{f1}^{(k)} = 1 - \hat{p}_{f1}^{(k)}$ . Given the initial value  $\theta^{(0)}$  of  $\theta$ , the above-mentioned two steps continue until the convergence criterion is satisfied. For example, the absolute differences between the estimates of the parameters at two consecutive iterations are all less than  $10^{-7}$ . The value of  $\theta$  obtained at the last iteration is taken as the MLE  $\hat{\theta}_1 = (\hat{p}_m, \hat{p}_{f1}, \hat{\rho}_1)$  of  $\theta$  under  $H_1$ .

Note that  $p_m = p_f$  and  $\rho = 0$  under  $H_0$ . Let  $p = p_m = p_f$ , the pooled allele frequency of  $M_1$ . Then,  $L(\theta)$  in Eq (1) can be rewritten as

$$L(\theta) \propto p^{n_{1m}+2n_{2f}+n_{1f}}(1-p)^{n_{0m}+n_{1f}+2n_{0f}}.$$

Thus, the MLE of  $p$  under  $H_0$  is  $\hat{p} = (n_{1m} + 2n_{2f} + n_{1f}) / (N_m + 2N_f)$ , the estimated pooled allele frequency of  $M_1$ . Let  $\hat{\theta}_0 = (\hat{p}, \hat{p}, 0)$ . Then, we can construct the following LRT to test for  $H_0$

$$LRT_0 = 2 \ln \frac{L(\hat{\theta}_1)}{L(\hat{\theta}_0)}, \tag{6}$$

which asymptotically follows a chi-square distribution with the degrees of freedom being 2 when the null hypothesis holds.

### Likelihood ratio test for equality of frequencies of the same allele in males and females

Once the null hypothesis ( $H_0: p_m = p_f$  and  $\rho = 0$ ) is rejected based on the result of Eq (6), we further need to consider the following two tests  $H_{01}: p_m = p_f$  and  $H_{02}: \rho = 0$ . Note that under the null hypothesis  $H_{01}: p_m = p_f = p$ ,  $\rho$  may not be zero and we need to estimate it. Let  $\phi = (p, \rho)$  and  $q = 1 - p$ . Thus, the corresponding likelihood function of complete data is

$$L_{c_1}(\phi) \propto p^{n_{1m}+2w_1+w_2+n_{1f}+w_4} (1-p)^{n_{0m}+w_2+n_{1f}+2w_3+w_4} \rho^{w_2+w_4} (1-\rho)^{n_{1f}}.$$

We use the following EM algorithm to estimate  $\phi$  under  $H_{01}$ . The corresponding formulas at iteration  $(k + 1)$  are as follows

$$\begin{aligned} \hat{p}_{01}^{(k+1)} &= \frac{E_{\phi^{(k)}}(2w_1 + w_2 | n_{2f}) + E_{\phi^{(k)}}(w_4 | n_{0f}) + n_{1f} + n_{1m}}{N_m + 2N_f}, \\ \hat{\rho}_{01}^{(k+1)} &= \frac{E_{\phi^{(k)}}(w_2 | n_{2f}) + E_{\phi^{(k)}}(w_4 | n_{0f})}{E_{\phi^{(k)}}(w_2 | n_{2f}) + E_{\phi^{(k)}}(w_4 | n_{0f}) + n_{1f}}, \end{aligned}$$

where  $\hat{p}_{01}^{(k+1)}$  and  $\hat{\rho}_{01}^{(k+1)}$  are respectively the MLEs of  $p$  and  $\rho$  at iteration  $(k + 1)$ , and  $\phi^{(k)} = (\hat{p}_{01}^{(k)}, \hat{\rho}_{01}^{(k)})$ .  $E_{\phi^{(k)}}(w_1 | n_{2f})$ ,  $E_{\phi^{(k)}}(w_2 | n_{2f})$ ,  $E_{\phi^{(k)}}(w_3 | n_{0f})$  and  $E_{\phi^{(k)}}(w_4 | n_{0f})$  in the above expressions are similar to  $E_{\theta^{(k)}}(w_1 | n_{2f})$ ,  $E_{\theta^{(k)}}(w_2 | n_{2f})$ ,  $E_{\theta^{(k)}}(w_3 | n_{0f})$  and  $E_{\theta^{(k)}}(w_4 | n_{0f})$  in Eqs (2)–(5), just replacing  $\hat{p}_{f1}^{(k)}$ ,  $\hat{q}_{f1}^{(k)}$  and  $\hat{\rho}_1^{(k)}$  in Eqs (2)–(5) by  $\hat{p}_{01}^{(k)}$ ,  $\hat{q}_{01}^{(k)}$  and  $\hat{\rho}_{01}^{(k)}$ , respectively. Let  $\hat{\theta}_{01} = (\hat{p}_{01}, \hat{\rho}_{01}, \hat{\rho}_{01})$ . Then, we propose the following test statistic  $LRT_1$  to test for the null hypothesis  $H_{01}: p_m = p_f$

$$LRT_1 = 2 \ln \frac{L(\hat{\theta}_1)}{L(\hat{\theta}_{01})}, \tag{7}$$

which approximately follows a chi-square distribution with the degree of freedom being 1 under  $H_{01}$ .

### Likelihood ratio test for inbreeding coefficient being zero

Note that under the null hypothesis  $H_{02}: \rho = 0$ ,  $p_m$  and  $p_f$  may be different from each other and we need to estimate them separately. Let  $\psi = (p_m, p_f)$  and  $L(\theta)$  in Eq (1) can be rewritten as

$$L_2(\psi) \propto p_m^{n_{1m}} q_m^{n_{0m}} p_f^{2n_{2f}+n_{1f}} q_f^{n_{1f}+2n_{0f}}.$$

Then, the MLEs of  $p_m$  and  $p_f$  are  $\hat{p}_m = n_{1m}/N_m$  and  $\hat{p}_f = (2n_{2f} + n_{1f})/(2N_f)$ , respectively, which are the same as zheng et al. [14]. Let  $\hat{\theta}_{02} = (\hat{p}_m, \hat{p}_f, 0)$ . As such, we develop the following test statistic to test for  $H_{02}: \rho = 0$

$$LRT_2 = 2 \ln \frac{L(\hat{\theta}_1)}{L(\hat{\theta}_{02})}, \tag{8}$$

which asymptotically follows a chi-square distribution with the degree of freedom being 1 under  $H_{02}$ . Just like the  $Z_2$  test statistic,  $LRT_2$  only uses female individuals in the sample because the terms based on male individuals in the numerator and the denominator of the fraction are the same, which can be reduced.

## Likelihood ratio tests via parametric bootstrap for $H_0$ and $H_{02}$

It should be noted from our simulation results (see the Results section) that the simulated type I error rates of  $LRT_0$  and  $LRT_{02}$  respectively for  $H_0$  and  $H_{02}$  are too conservative. On the other hand, several studies showed that the likelihood ratio tests may typically not follow a chi-square distribution asymptotically [31, 32], and hence their exact distributions can be obtained by Monte Carlo simulation [33]. Accordingly, we make use of parametric bootstrap techniques to evaluate the size and power of these two methods. For convenience, we denote these methods via parametric bootstrap by  $LRT_{0b}$  and  $LRT_{2b}$ , respectively. We begin by describing the implementation steps for  $LRT_{0b}$  as follows:

1. For a collected sample of size  $N$  with  $N_m$  males and  $N_f$  females, calculate the value of  $LRT_0$ ;
2. Compute the estimated pooled allele frequency  $\hat{p}$  based on the sample as follows:  

$$\hat{p} = (n_{1m} + 2n_{2f} + n_{1f}) / (N_m + 2N_f);$$
3. Based on  $\hat{p}$ , calculate the frequencies of three genotypes  $M_1M_1$ ,  $M_1M_2$  and  $M_2M_2$  in females under  $H_0$  in the following:  $\hat{p}^2$ ,  $2\hat{p}\hat{q}$  and  $\hat{q}^2$ , respectively, where  $\hat{q} = 1 - \hat{p}$ ;
4. According to  $\hat{p}$  and  $\hat{q}$ , regenerate the alleles of  $N_m$  males; based on  $\hat{p}^2$ ,  $2\hat{p}\hat{q}$  and  $\hat{q}^2$ , regenerate the genotypes of  $N_f$  females;
5. Calculate the value of  $LRT_0$  based on the new  $N_m$  males and  $N_f$  females, denoted by  $LRT_0^*$ ;
6. Repeat Steps 4 and 5  $B$  times, which results in  $B$  test statistics  $LRT_0^{1*}$ ,  $LRT_0^{2*}$ ,  $\dots$ ,  $LRT_0^{B*}$ ;
7. The  $P$ -value of the original  $LRT_0$  can be estimated as

$$\hat{P} - \text{value} = \frac{1}{B} \sum_{i=1}^B I_{\{LRT_0^{i*} > LRT_0\}}.$$

For  $LRT_{2b}$ , we can conduct the steps similar to those mentioned above. Firstly, after obtaining the value of  $LRT_2$ , calculate the frequencies of three genotypes  $M_1M_1$ ,  $M_1M_2$  and  $M_2M_2$  in females under  $H_{02}$  in the following:  $\hat{p}_f^2$ ,  $2\hat{p}_f\hat{q}_f$  and  $\hat{q}_f^2$ , respectively, with  $\hat{p}_f = (2n_{2f} + n_{1f}) / (2N_f)$ . The alleles of  $N_m$  males stay the same as the original sample and only regenerate the genotypes of  $N_f$  females according to  $\hat{p}_f^2$ ,  $2\hat{p}_f\hat{q}_f$  and  $\hat{q}_f^2$ . Then, carry out the similar procedures of Steps 4–7 and we can obtain the the estimated  $P$ -value of  $LRT_2$ .

## Software implementation

We have written the XHWE software with R (<http://www.r-project.org>), which includes the eight test statistics:  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$ . The R package named XHWE is available on CRAN (<http://cran.r-project.org/web/packages/XHWE/>). The initial values of  $p_m$ ,  $p_f$ ,  $p$  and  $\rho$  in the EM algorithms are taken to be  $n_{1m}/N_m$ ,  $(2n_{2f} + n_{1f})/(2N_f)$ ,  $(n_{1m} + 2n_{2f} + n_{1f})/(N_m + 2N_f)$  and 0.02, respectively. The convergence criterion is that the absolute differences between the estimates of the parameters at two consecutive iterations are all less than  $10^{-7}$  for the LRT-type statistics. The default maximum number of iterations is 1000. The input data file is the standard pedigree data. The XHWE software only uses the founders with genotypes available in it and will analyze marker loci one by one. The software outputs the values of all the test statistics and the corresponding  $P$ -values. Also, the XHWE software outputs the estimates of all the parameters under both the null and alternative hypotheses for each test statistic. The parameter estimates under the alternative hypothesis for the LRT-type test



statistics are the same. However, under the respective null hypotheses of the LRT-type test statistics, the estimates may be different. It should be noted that the estimates of  $p_m$  and  $p_f$  under the null hypothesis of  $H_{02}$  in this article and those in zheng et al. [14] are the same, respectively. The output results will be automatically saved in the text file named “results.txt”.

### Simulation settings

Simulation study is conducted to assess the performance of the proposed  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$  and  $Z_0$  test statistics and to compare them with the existing  $Z_1$  and  $Z_2$  under various simulation settings which are similar to those in zheng et al. [14]. The allele frequency  $p_m$  in males takes two values: 0.3 and 0.5. When  $p_m$  is fixed, the value of  $p_f$  in females is taken as  $p_f = p_m + \epsilon$ , where  $\epsilon = 0, \pm 0.04$  and  $\pm 0.05$ . The inbreeding coefficient  $\rho$  in females is set at 0 to 0.1 in increment of 0.05. The sample size is taken as 800 and 1200 with the ratio  $r = N_m : N_f$  being 2:1, 1.5:1, 1:1, 1:1.5 and 1:2. As mentioned earlier, when  $p_m = p_f$  and  $\rho = 0$ , the size of all the eight test statistics is simulated; when  $p_m = p_f$  and  $\rho > 0$ , the size of  $LRT_1$  and  $Z_1$  is gotten; when  $p_m \neq p_f$  and  $\rho = 0$ , the size of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  is obtained. Otherwise, we simulate the corresponding powers. In addition, it should be noted that for the fixed sample size (800 or 1200) simulated above, the powers of all the three test statistics  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  for  $H_{02} : \rho = 0$  are not so large, from our simulation results below. On the other hand, these three test statistics only use female individuals. As such, we further obtain the sample size  $N_f$  required for  $LRT_{2b}$  to gain 80% simulated power and then simulate the size and powers of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  under this sample size. To investigate how population structure affects the proposed methods, we also consider the following population stratification model with two subpopulations in our simulation study.  $p_m = 0.3$  (0.5),  $p_f = p_m + \epsilon$ ,  $\epsilon = 0, \pm 0.04$  and  $\pm 0.05$  in the first (second) subpopulation and the  $\epsilon$  values are respectively denoted by  $\epsilon_1$  and  $\epsilon_2$ . Assume that  $\rho = 0$  in each subpopulation, and the ratio of each subpopulation constructing the population is set to 0.5. The sample size is taken to be 1800, where each individual is a female or a male with equal probability. Note that under population stratification, the null hypothesis  $H_0 : p_m = p_f$  and  $\rho = 0$  is generally not true. Thus, we use the population stratification model to study the powers of the proposed methods. The significance level is fixed at 5% and 10000 replications are simulated under each simulation setting. For  $LRT_{0b}$  and  $LRT_{2b}$  via parametric bootstrap,  $B$  is set to be 1000. Finally, to compare the efficiency of the parameter estimates of the proposed EM algorithms with those in zheng et al. [14] for each simulation setting, we use the RMSEs and biases to assess the accuracy of the parameter estimates, where  $RMSE = \sqrt{[Bias(\hat{\beta})]^2 + Var(\hat{\beta})}$  and  $Bias = E(\hat{\beta}) - \beta$ , and  $\beta$  is the parameter which needs to estimate.

## Results

### Simulation results

Table 1 lists the simulated size of  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  under  $H_0 : p_m = p_f = p$  and  $\rho = 0$  with  $N = 800$  and  $1200$  and  $p = 0.3$  and  $0.5$  for different values of  $r = N_m : N_f$ . According to the table, the size of  $LRT_1$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  is close to the nominal 5% level, while the size of  $LRT_0$  and  $LRT_2$  is too conservative. However, after the parametric bootstrap technique,  $LRT_{0b}$  and  $LRT_{2b}$  stay close to the nominal 5% level.

Fig 1 gives the simulated powers of the eight test statistics against  $r$  under  $H_1 : p_m \neq p_f$  and  $\rho > 0$  for different values of  $\rho$  (0.05 and 0.1) and  $N$  (800 and 1200), having  $p_m = 0.3$  and  $p_f = 0.35$ . It is shown in the figure that  $LRT_{0b}$  is more powerful than  $LRT_0$  and  $Z_0$ , and  $LRT_0$  and  $Z_0$  have the similar performance in power (Fig 1a-1d in the first row), regarded of the inbreeding coefficient  $\rho$ , the sample size  $N$  and the ratio  $r$ .  $LRT_1$  and  $Z_1$  have almost the same performance in



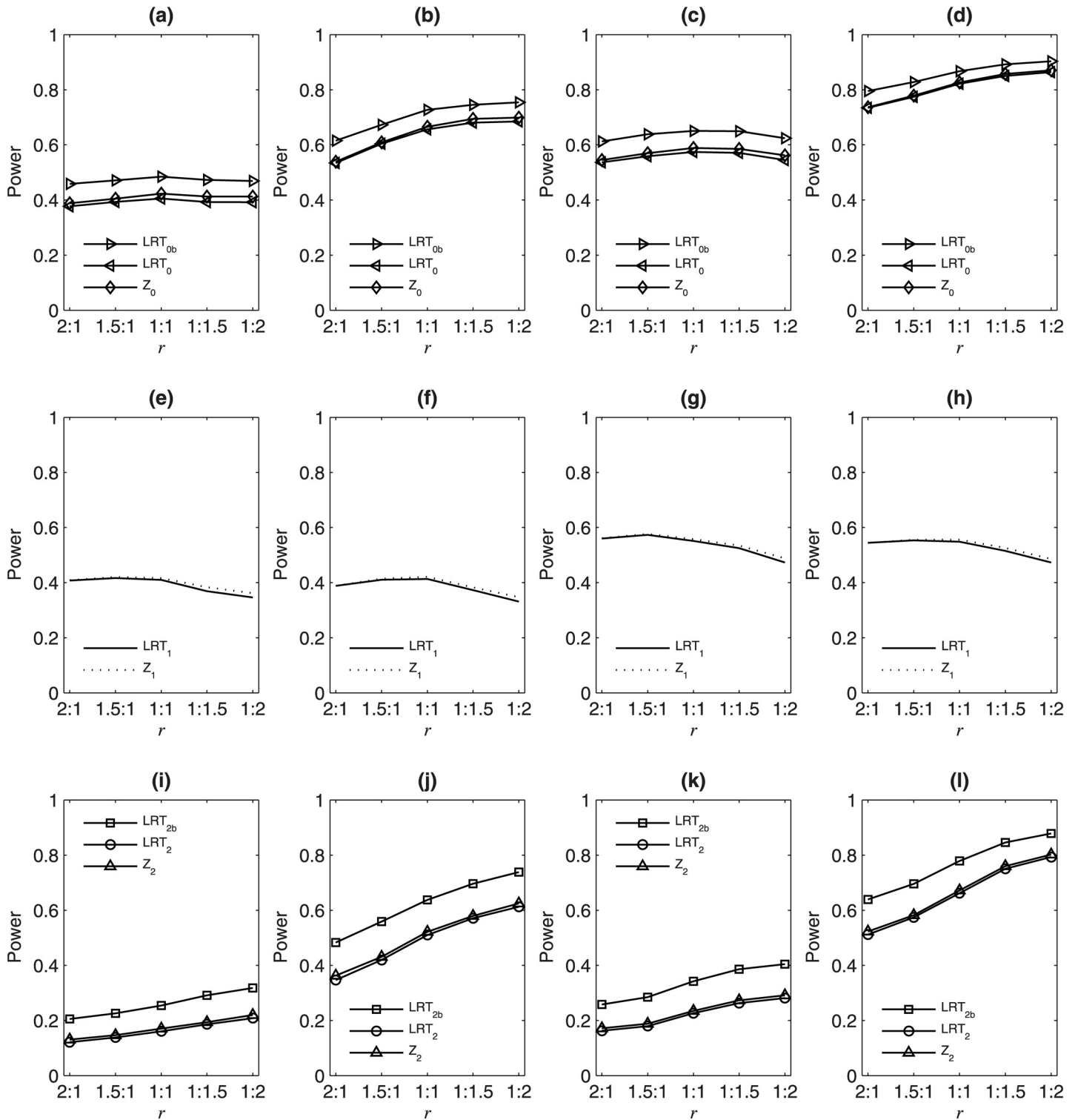
**Table 1. Simulated size (in %) of  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  under  $H_0 : p_m = p_f = p$  and  $\rho = 0$  with  $N = 800$  and  $1200$  for different values of  $r$  and  $p$ .**

$N$	$r$	$p$	$LRT_0$	$LRT_{0b}$	$LRT_1$	$LRT_2$	$LRT_{2b}$	$Z_0$	$Z_1$	$Z_2$	
800	2:1	0.3	3.01	4.81	5.02	1.91	4.87	4.83	5.22	4.83	
	2:1	0.5	2.98	4.97	5.02	2.28	4.99	5.13	5.19	5.13	
	1.5:1	0.3	2.92	4.81	4.74	2.19	4.75	4.99	4.93	4.99	
	1.5:1	0.5	3.07	4.93	4.83	2.22	4.98	5.02	4.99	5.02	
	1:1	0.3	3.17	5.05	4.74	2.59	5.36	4.82	4.81	4.82	
	1:1	0.5	3.30	4.99	5.33	2.40	5.20	5.16	5.34	5.16	
	1:1.5	0.3	3.05	5.18	5.09	2.40	5.11	5.09	5.28	5.09	
	1:1.5	0.5	3.39	5.18	5.03	2.49	5.34	5.19	5.07	5.19	
	1:2	0.3	3.13	4.89	4.77	2.18	4.81	5.13	4.89	5.13	
	1:2	0.5	3.12	4.85	4.65	2.32	5.13	5.23	4.78	5.23	
	1200	2:1	0.3	3.42	5.31	4.84	2.35	5.07	5.47	4.97	5.47
		2:1	0.5	3.45	5.38	4.76	2.48	5.15	5.38	5.01	5.38
		1.5:1	0.3	2.91	4.84	4.84	2.30	5.12	4.83	5.02	5.16
		1.5:1	0.5	3.36	5.31	5.29	2.45	5.35	5.38	5.42	5.38
1:1		0.3	2.88	4.77	5.05	2.15	4.73	4.73	5.18	4.73	
1:1		0.5	3.04	5.07	5.22	2.01	4.79	4.94	5.30	4.94	
1:1.5		0.3	2.93	4.97	4.75	2.25	4.98	4.98	4.87	4.98	
1:1.5		0.5	3.08	4.83	5.06	2.24	4.86	4.87	5.12	4.87	
1:2		0.3	3.13	4.98	4.83	2.39	5.31	5.03	4.92	5.03	
1:2		0.5	3.24	5.06	4.86	2.54	5.38	5.05	4.91	5.05	

doi:10.1371/journal.pone.0145032.t001

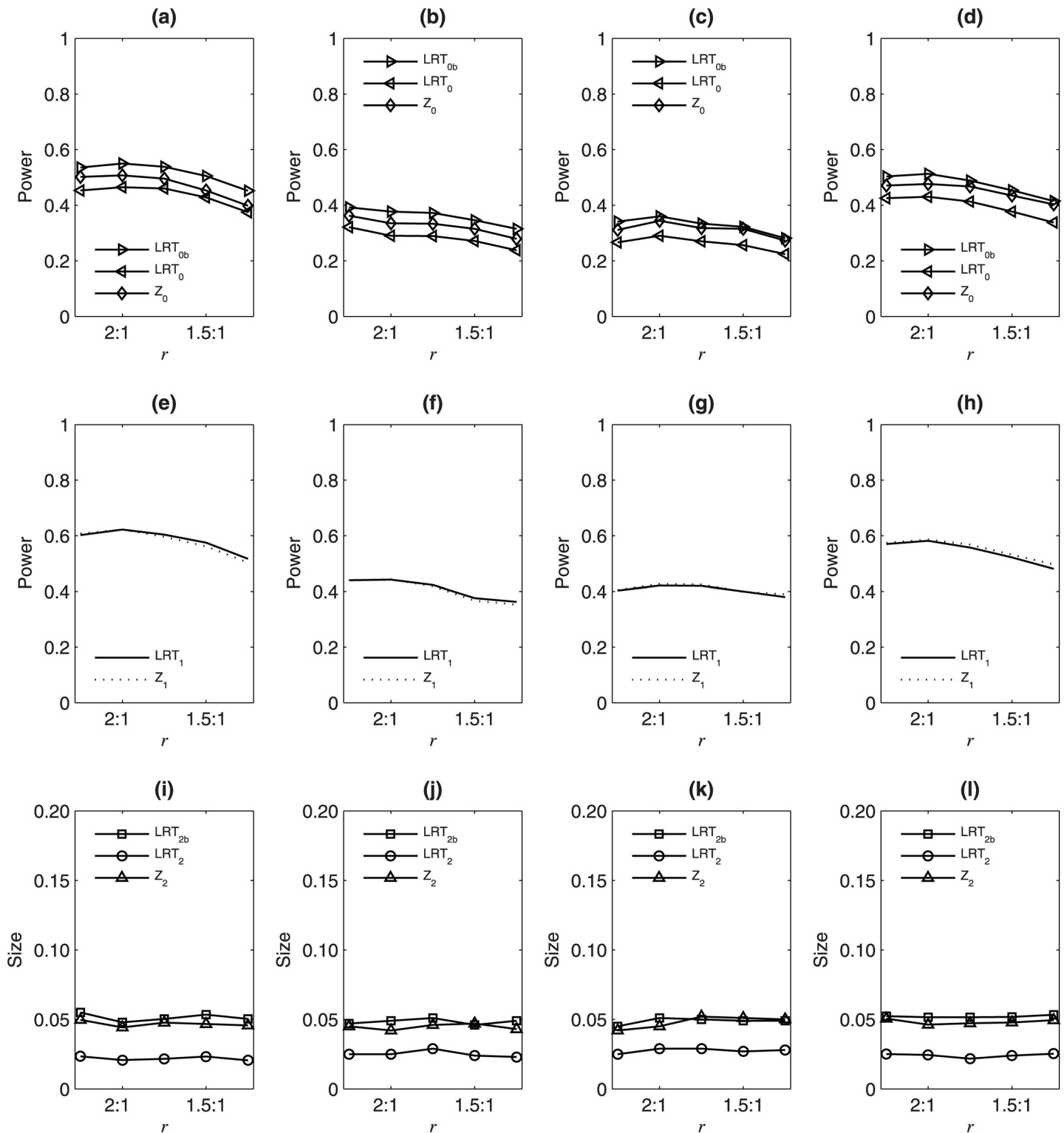
power (Fig 1e-1h in the second row).  $LRT_{2b}$  has much more power than  $LRT_2$  and  $Z_2$ , and  $LRT_2$  is a little less powerful than  $Z_2$  (Fig 1i-1l in the third row). The powers of  $LRT_1$  and  $Z_1$  are not so affected by the different values of  $r$ , while  $LRT_0$ ,  $LRT_{0b}$ ,  $Z_0$ ,  $LRT_{2b}$ ,  $LRT_2$  and  $Z_2$  are more and more powerful with the number of female individuals increasing ( $r$  changing from 2:1 to 1:2) when other parameters are fixed. We also find that the powers of  $LRT_0$ ,  $LRT_{0b}$ ,  $Z_0$ ,  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  appear great reaction to the different values of  $\rho$  when  $N$  is fixed. Specially, their powers under  $\rho = 0.1$  (subplots in the second and fourth columns, respectively) are much larger than those under  $\rho = 0.05$  (subplots in the first and third columns, respectively). However, the powers of  $LRT_1$  and  $Z_1$  are almost not influenced by  $\rho$ . Further, it can be seen in Fig 1 that  $LRT_0$ ,  $LRT_{0b}$  and  $Z_0$  with two degrees of freedom (subplots in the first row) are much more powerful than  $LRT_1$ ,  $Z_1$ ,  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  with one degree of freedom (subplots in the second and third rows). This is because the true model is  $p_m \neq p_f$  and  $\rho > 0$ . In addition, when the sample size changes from 800 (subplots in the first and second columns) to 1200 (subplots in the third and fourth columns), all the test statistics are much more powerful.

Fig 2 displays the simulated size/powers of the eight test statistics against  $r$  under  $H_{02} : \rho = 0$  for different values of  $p_f$  having  $p_m = 0.3$  and  $N = 1200$ . The results in the third row of the figure are the size of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$ , while those in the first and the second rows of the figure are the powers of  $LRT_0$ ,  $LRT_{0b}$  and  $Z_0$ , and those of  $LRT_1$  and  $Z_1$ , respectively. It is shown in the figure that the size of  $LRT_{2b}$  and  $Z_2$  maintains close to the nominal 5% level, while  $LRT_2$  is too conservative. As for the tests for  $H_{01} : p_m = p_f$ ,  $LRT_1$  and  $Z_1$  almost have the same simulated power just like Fig 1. On the other hand, the powers of  $LRT_0$ ,  $LRT_{0b}$ ,  $Z_0$ ,  $LRT_1$  and  $Z_1$  are not so affected by the ratio  $r$ . However, their powers are greatly influenced by the absolute difference  $|\epsilon| = |p_m - p_f|$ . Specifically, their powers under  $p_f = 0.25$  and  $p_f = 0.35$  are much larger than those under  $p_f = 0.26$  and  $p_f = 0.34$ . In addition, when the simulation setting is fixed,  $LRT_1$  and



**Fig 1. Simulated powers of LRT<sub>0</sub>, LRT<sub>0b</sub>, LRT<sub>1</sub>, LRT<sub>2</sub>, LRT<sub>2b</sub>, Z<sub>0</sub>, Z<sub>1</sub> and Z<sub>2</sub> against  $r = N_m : N_f$  under  $H_1 : p_m \neq p_f$  and  $\rho > 0$  based on 10000 replicates with  $p_m = 0.3$  and  $p_f = 0.35$ . In the first column:  $\rho = 0.05$  and  $N = 800$ ; in the second column:  $\rho = 0.1$  and  $N = 800$ ; in the third column:  $\rho = 0.05$  and  $N = 1200$ ; in the fourth column:  $\rho = 0.1$  and  $N = 1200$ . In the first row, the powers of LRT<sub>0</sub>, LRT<sub>0b</sub> and Z<sub>0</sub> for  $H_0 : p_m = p_f$  and  $\rho = 0$ ; in the second row, the powers of LRT<sub>1</sub> and Z<sub>1</sub> for  $H_{01} : p_m = p_f$ ; in the third row, the powers of LRT<sub>2</sub>, LRT<sub>2b</sub> and Z<sub>2</sub> for  $H_{02} : \rho = 0$ .**

doi:10.1371/journal.pone.0145032.g001



**Fig 2. Simulated size/powers of  $LRT_0$ ,  $LRT_{ob}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  against  $r = N_m : N_f$  under  $H_{02} : \rho = 0$  based on 10000 replicates with  $\rho_m = 0.3$  and  $N = 1200$ .** In the first column:  $\rho_f = 0.25$ ; in the second column:  $\rho_f = 0.26$ ; in the third column:  $\rho_f = 0.34$ ; in the fourth column:  $\rho_f = 0.35$ . In the first row, the powers of  $LRT_0$ ,  $LRT_{ob}$  and  $Z_0$  for  $H_0 : \rho_m = \rho_f$  and  $\rho = 0$ ; in the second row, the powers of  $LRT_1$  and  $Z_1$  for  $H_{01} : \rho_m = \rho_f$ ; in the third row, the size of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  for  $H_{02} : \rho = 0$ .

doi:10.1371/journal.pone.0145032.g002

$Z_1$  with one degree of freedom are a little more powerful than  $LRT_0$ ,  $LRT_{0b}$  and  $Z_0$  with two degrees of freedom, because the true model is  $p_m \neq p_f$  and  $\rho = 0$ . By comparing Fig 2d ( $\rho = 0$ ), Fig 1c ( $\rho = 0.05$ ) and Fig 1d ( $\rho = 0.1$ ) under  $N = 1200$ ,  $p_m = 0.3$  and  $p_f = 0.35$ ,  $LRT_0$ ,  $LRT_{0b}$  and  $Z_0$  are more and more powerful with  $\rho$  increasing.

Figs A–G in S1 File show the corresponding results under other simulation settings with  $p_m \neq p_f$  and  $\rho > 0$ , which are similar to those in Fig 1. Figs H and I in S1 File plot the corresponding results under  $p_m = p_f$  and  $\rho > 0$ , and Figs J–L in S1 File give the corresponding results under  $p_m \neq p_f$  and  $\rho = 0$ . The more details refer to S1 File.

Table 2 shows the simulated size of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  for  $H_{02} : \rho = 0$  for different values of  $p_f$ , having  $N_m = 0$  under the sample sizes  $N_f$  required for  $LRT_{2b}$  to obtain 80% simulated power. Table 3 lists the simulated powers under these sample sizes for different values of  $p_f$ , having  $\rho = 0.05$  and  $0.1$ . From Table 2, we can see that the type I error rates of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$  are close to the nominal significance level of 5%. It is shown in Table 3 that the power of  $LRT_{2b}$  attains to about 80%, and the difference in power between  $LRT_{2b}$  and  $Z_2$  is about 10%.

Tables A–J in S1 File list the RMSEs and biases of the estimates of  $p_m$ ,  $p_f$ , the pooled allele frequency  $p$  and  $\rho$  for different values of  $p_m$ ,  $p_f$ ,  $\rho$ ,  $r$  and  $N$ . It should be noted that the estimate of  $p_m$  based on the EM algorithm is the same as zheng et al. [14]. Further, the estimates  $\hat{p}_{f1}$  and  $\hat{p}_{01}$  of  $p_f$  and  $p$  based on the EM algorithms have the similar RMSEs and biases as those from zheng et al. [14], respectively. However, when we focus on the estimate of  $\rho$ , we find that although the biases of  $\hat{\rho}_1$  and  $\hat{\rho}_{01}$  based on the EM algorithms are larger than  $\hat{\rho}_z$  in zheng et al. [14] for some cases, the RMSEs of  $\hat{\rho}_1$  and  $\hat{\rho}_{01}$  are smaller than  $\hat{\rho}_z$  for all the simulation settings.

Table 4 displays the simulated size/powers of  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  under the population stratification model. When  $\epsilon_1 = \epsilon_2 = 0$ , the size of  $LRT_1$  and  $Z_1$  is obtained. Further, note that the ratios of two subpopulations in the whole population are equal. As such,  $\epsilon_1 = -\epsilon_2$  will also cause the size of  $LRT_1$  and  $Z_1$ . Under other simulation settings, we get the powers of the eight test statistics. To investigate whether or not the population stratification model

**Table 2. Simulated size (in %) of  $LRT_2$ ,  $LRT_{2b}$  and  $Z_2$ , having  $N_m = 0$  and  $\rho = 0$ .**

$N_f$	$p_f$	$LRT_2$	$LRT_{2b}$	$Z_2$
2500	0.20	2.27	5.18	4.84
	0.25	2.27	4.96	4.89
	0.30	2.43	5.15	5.13
	0.35	2.31	4.99	5.14
	0.40	2.25	4.96	4.70
	0.45	2.43	5.05	4.93
	0.50	2.54	5.03	5.06
	0.55	2.38	5.26	4.86
	0.60	2.49	5.11	5.10
	650	0.20	2.14	4.98
0.25		2.03	4.62	4.82
0.30		2.53	4.91	5.20
0.35		2.45	5.05	5.11
0.40		2.18	4.72	4.54
0.45		2.04	4.84	4.65
0.50		2.48	4.98	5.14
0.55		2.30	4.74	5.12
0.60		2.27	5.01	4.77

doi:10.1371/journal.pone.0145032.t002

**Table 3. Simulated powers (in %) of LRT<sub>2</sub>, LRT<sub>2b</sub> and Z<sub>2</sub>, having N<sub>m</sub> = 0.**

N <sub>f</sub>	ρ	p <sub>f</sub>	LRT <sub>2</sub>	LRT <sub>2b</sub>	Z <sub>2</sub>
2500	0.05	0.20	68.2	79.0	69.7
	0.05	0.25	69.1	79.4	69.9
	0.05	0.30	69.4	79.9	70.2
	0.05	0.35	69.8	80.2	70.3
	0.05	0.40	70.0	80.6	70.4
	0.05	0.45	69.3	79.9	69.6
	0.05	0.50	70.6	80.8	71.5
	0.05	0.55	71.2	81.0	71.5
	0.05	0.60	70.2	80.6	70.5
650	0.10	0.20	68.1	78.9	70.3
	0.10	0.25	69.2	79.9	70.8
	0.10	0.30	69.9	80.9	71.0
	0.10	0.35	70.3	80.5	71.1
	0.10	0.40	71.1	81.1	71.8
	0.10	0.45	71.9	81.9	72.5
	0.10	0.50	71.1	81.6	72.1
	0.10	0.55	70.7	81.4	71.3
	0.10	0.60	70.8	81.9	71.6

doi:10.1371/journal.pone.0145032.t003

causes excess homozygosity, we save the values of 10000 ρ estimates for each estimation method ( $\hat{\rho}_1, \hat{\rho}_{01}$  or  $\hat{\rho}_z$ ). Then, calculate the corresponding mean and standard deviation (SD), which are also listed in Table 4. The results show that the population stratification model indeed leads to the positive inbreeding coefficient (i.e., excess homozygosity), which is consistent with Overall and Nichols [24]. The mean  $\hat{\rho}$  values ( $\hat{\rho}_1$  and  $\hat{\rho}_{01}$ ) using the EM algorithm are a little larger than  $\hat{\rho}_z$  proposed in zheng et al. [14], while  $\hat{\rho}_1$  and  $\hat{\rho}_{01}$  have less standard deviation. On the other hand, the size of LRT<sub>1</sub> and Z<sub>1</sub> is close to the nominal significance level of 5%. The power of LRT<sub>0b</sub> is larger than LRT<sub>0</sub> and Z<sub>0</sub>, and LRT<sub>0</sub> and Z<sub>0</sub> have the similar powers, irrespective of the  $\epsilon_1$  and  $\epsilon_2$  values. LRT<sub>1</sub> and Z<sub>1</sub> have almost the same powers. LRT<sub>2b</sub> is much more powerful than LRT<sub>2</sub> and Z<sub>2</sub>, and the power of LRT<sub>2</sub> is a little smaller than Z<sub>2</sub>. If  $\epsilon_1$  is fixed and  $\epsilon_2$  is changed, the ρ estimate increases with  $\epsilon_2$  increasing, and hence LRT<sub>2</sub>, LRT<sub>2b</sub> and Z<sub>2</sub> are more and more powerful; if  $\epsilon_2$  is fixed and  $\epsilon_1$  is changed, the ρ estimate decreases with  $\epsilon_1$  increasing, and hence LRT<sub>2</sub>, LRT<sub>2b</sub> and Z<sub>2</sub> are less and less powerful. This may be caused by  $p_m$  being taken to be 0.3 and 0.5 in the first and second subpopulations, respectively.

### Application to RA data

We apply the proposed methods to the RA dataset from North American Rheumatoid Arthritis Consortium for studying their practicability, which is available from Genetic Analysis Workshop 15. In this dataset, there are 1217 families. Note that many individuals' genotypes are missing. On the other hand, to obtain a sample of which all the individuals are independent, we only select the available founders in this dataset, which results in a sample composed of 369 founders ( $N_m = 112$  and  $N_f = 257$ ) in the analysis. 293 SNP markers on X chromosome for each founder are included in this application. The significance level is fixed at  $\alpha = 5\%$ . Table 5 gives the corresponding results based on the P-values of LRT<sub>0b</sub>, LRT<sub>1</sub>, LRT<sub>2b</sub>, Z<sub>0</sub>, Z<sub>1</sub> and Z<sub>2</sub>. From Table 5, LRT<sub>0b</sub> identified 6 loci which Z<sub>0</sub> did not identify, and Z<sub>0</sub> identified 4 additional loci. One locus is detected by LRT<sub>1</sub> that is not found by Z<sub>1</sub>, and 4 additional loci are detected by

**Table 4. Mean and standard deviation (SD) of  $\rho$  estimates over 10000 replications, and simulated size/powers (in %) of  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  under population stratification model.**

$\epsilon$		$\hat{\rho}_1$		$\hat{\rho}_{01}$		$\hat{\rho}_z$		Power							
$\epsilon_1^a$	$\epsilon_2^b$	Mean	SD	Mean	SD	Mean	SD	$LRT_0$	$LRT_{0b}$	$LRT_1$	$LRT_2$	$LRT_{2b}$	$Z_0$	$Z_1$	$Z_2$
-0.05	-0.05	0.043	0.031	0.046	0.032	0.042	0.034	72.3	78.6	72.1	24.1	37.0	72.6	71.5	25.0
	-0.04	0.050	0.031	0.052	0.032	0.049	0.034	67.8	74.4	63.4	31.0	43.9	67.7	63.0	31.6
	0.00	0.067	0.032	0.068	0.032	0.067	0.033	54.8	63.4	22.7	51.7	65.2	55.3	22.5	52.5
	0.04	0.088	0.034	0.088	0.034	0.087	0.034	65.0	72.3	4.7	73.6	82.8	65.6	4.7	74.5
	0.05	0.093	0.035	0.093	0.035	0.093	0.035	70.9	76.3	4.1	78.7	86.2	71.3	4.1	79.0
-0.04	-0.05	0.039	0.029	0.041	0.030	0.037	0.033	60.5	69.0	63.2	19.2	28.5	60.9	63.2	19.8
	-0.04	0.045	0.030	0.046	0.031	0.043	0.033	57.6	63.8	50.5	25.6	37.6	57.6	49.9	26.2
	0.00	0.061	0.033	0.062	0.033	0.060	0.034	42.2	51.1	17.0	44.5	57.7	42.6	17.0	45.0
	0.04	0.081	0.033	0.081	0.033	0.081	0.034	57.4	64.0	4.2	65.9	77.9	58.1	4.3	66.4
	0.05	0.088	0.033	0.088	0.033	0.088	0.033	65.2	72.5	5.0	74.7	85.2	65.8	5.0	75.7
0.00	-0.05	0.029	0.027	0.030	0.027	0.025	0.033	21.8	29.0	23.0	11.0	19.0	22.5	22.9	12.1
	-0.04	0.030	0.027	0.031	0.027	0.026	0.033	18.9	24.6	17.3	12.5	20.0	19.6	17.2	12.9
	0.00	0.043	0.029	0.043	0.029	0.041	0.032	17.7	24.0	4.3	23.1	34.9	18.2	4.3	23.9
	0.04	0.058	0.032	0.058	0.032	0.058	0.033	42.3	50.6	19.0	40.0	54.1	43.1	19.0	40.6
	0.05	0.063	0.032	0.063	0.032	0.063	0.033	49.4	57.4	23.3	46.2	59.5	50.1	23.5	46.9
0.04	-0.05	0.019	0.023	0.020	0.023	0.012	0.032	6.7	9.4	6.8	4.8	10.0	7.6	6.9	6.1
	-0.04	0.022	0.024	0.022	0.025	0.014	0.034	6.3	9.0	4.7	7.1	11.7	7.0	4.7	7.7
	0.00	0.031	0.028	0.031	0.028	0.026	0.034	18.0	23.7	17.5	11.8	20.7	18.9	17.5	12.8
	0.04	0.041	0.031	0.041	0.031	0.039	0.034	52.1	61.9	51.8	21.2	32.0	52.7	52.1	21.5
	0.05	0.046	0.031	0.047	0.031	0.045	0.034	61.7	69.5	58.6	27.1	38.9	62.1	58.8	27.6
0.05	-0.05	0.018	0.023	0.018	0.023	0.008	0.034	4.1	7.2	4.9	4.5	8.4	5.2	5.0	5.5
	-0.04	0.020	0.023	0.020	0.023	0.011	0.034	6.0	8.4	5.2	4.2	10.1	7.5	5.2	5.9
	0.00	0.028	0.028	0.028	0.028	0.022	0.035	22.1	28.2	24.1	10.4	16.9	22.9	24.2	11.2
	0.04	0.036	0.028	0.037	0.028	0.034	0.032	59.5	65.7	61.6	17.0	27.1	60.0	61.9	17.7
	0.05	0.042	0.031	0.043	0.030	0.040	0.033	68.1	74.1	67.2	22.6	32.1	68.3	67.6	23.4

<sup>a</sup>  $\epsilon$  in the first subpopulation.

<sup>b</sup>  $\epsilon$  in the second subpopulation.

doi:10.1371/journal.pone.0145032.t004

$Z_1$ . There are 12 loci identified by  $LRT_{2b}$ , which can not be identified by  $Z_2$ , and only 2 additional loci are identified by  $Z_2$ . However, there exist multiple testing problems because we simultaneously analyze 293 loci. So, Bonferroni correction is used ( $\alpha' = 0.05/293 = 1.71 \times 10^{-4}$ ) and there is no statistically significant result to occur. The more details can be found in Tables K–M in [S1 File](#).

To investigate the computational efficiency of the XHWE software, we implement the code with the default arguments for this dataset (1217 families and 293 SNPs), on a HP 2311f personal computer (Microsoft Windows 7 Enterprise (Service Pack 1), 4GB of RAM and 3.40 GHz Intel(R) Core(TM) i7 Duo processor) and record its computational time. This process needs 977 seconds. Therefore, on the average, the running time for a single SNP is about 3.3 seconds. For the genome-wide case, for example, one would analyze 200000 SNP markers on X chromosome for the family sample of the type mentioned above, which would lead to 1600000 tests for the hypotheses with running time being about 7.6 days on the personal computer of this type.

**Table 5. LRT<sub>0b</sub>, LRT<sub>1</sub>, LRT<sub>2b</sub>, Z<sub>0</sub>, Z<sub>1</sub> and Z<sub>2</sub> results of application to rheumatoid arthritis data at 5% level.**

<b>A. Contingency table showing LRT<sub>0b</sub> and Z<sub>0</sub> results at 5% level.</b>			
	$P_{Z_0} < 0.05$	$P_{Z_0} \geq 0.05$	<b>Total</b>
$P_{LRT_{0b}} < 0.05$	11	6	17
$P_{LRT_{0b}} \geq 0.05$	4	272	276
<b>Total</b>	15	278	293
<b>B. Contingency table showing LRT<sub>1</sub> and Z<sub>1</sub> results at 5% level.</b>			
	$P_{Z_1} < 0.05$	$P_{Z_1} \geq 0.05$	<b>Total</b>
$P_{LRT_1} < 0.05$	9	1	10
$P_{LRT_1} \geq 0.05$	4	279	283
<b>Total</b>	13	280	293
<b>C. Contingency table showing LRT<sub>2b</sub> and Z<sub>2</sub> results at 5% level.</b>			
	$P_{Z_2} < 0.05$	$P_{Z_2} \geq 0.05$	<b>Total</b>
$P_{LRT_{2b}} < 0.05$	14	12	26
$P_{LRT_{2b}} \geq 0.05$	2	265	267
<b>Total</b>	16	277	293

doi:10.1371/journal.pone.0145032.t005

## Discussion

The existing  $Z_1$  and  $Z_2$  tests were respectively proposed to test for  $H_{01} : p_m = p_f$  and  $H_{02} : \rho = 0$ . However, we find that there is no simulation study conducted to assess the validity of  $Z_1$  and  $Z_2$  and their performance [14]. Further, there is no existing method to simultaneously test for  $H_0 : p_m = p_f$  and  $\rho = 0$ . Therefore, in this article, we first combine these two test statistics and suggest  $Z_0 = Z_1 + Z_2$  to test for the equality of the frequencies of the same allele in males and females and the zero inbreeding coefficient on X chromosome based on the collected sample, because  $Z_1$  and  $Z_2$  are independent of each other. What's more, for the purpose of improving the test power, we propose several LRT-type test statistics. Firstly, we write out the likelihood functions under  $H_0 : p_m = p_f$  and  $\rho = 0$  and  $H_1 : p_m \neq p_f$  or  $\rho > 0$  at a single SNP locus on X chromosome, respectively. Then, we obtain the MLEs of the male allele frequency, the female allele frequency and the inbreeding coefficient by the EM algorithms, where we use the RMSE and bias to assess the accuracy of the MLEs of these unknown parameters and construct the corresponding likelihood ratio test (LRT<sub>0</sub>) statistic under the null hypothesis  $H_0$ . If  $H_0$  is statistically rejected, we further develop two LRT-type test statistics LRT<sub>1</sub> and LRT<sub>2</sub> respectively for  $H_{01} : p_m = p_f$  and  $H_{02} : \rho = 0$ . Note that LRT<sub>0</sub> and LRT<sub>2</sub> are too conservative from the simulated results. So, we use parametric bootstrap techniques and propose the LRT<sub>0b</sub> and LRT<sub>2b</sub> test statistics. We simulate the data under different parameter settings. Simulation results show that the proposed bootstrap-based methods LRT<sub>0b</sub> and LRT<sub>2b</sub>, LRT<sub>1</sub>,  $Z_0$  and the existing  $Z_1$  and  $Z_2$  control the type I error rates well under the respective null hypothesis. Power comparison demonstrates that LRT<sub>0b</sub> is more powerful than both LRT<sub>0</sub> and  $Z_0$ . Under  $\rho > 0$ , LRT<sub>2b</sub> has much more power than LRT<sub>2</sub> and  $Z_2$ , and LRT<sub>2</sub> is a little less powerful than  $Z_2$ . In addition, LRT<sub>1</sub> and  $Z_1$  almost have the same power under  $p_m \neq p_f$ .

As for the parameter estimates, the estimate of  $p_m$  based on the EM algorithm is the same as that in zheng et al. [14]. Further, the estimates  $\hat{p}_{f1}$  and  $\hat{p}_{01}$  of  $p_f$  and the pooled allele frequency  $p$  based on the EM algorithms have the RMSE and bias similar to those from zheng et al. [14], respectively. However, although the biases of  $\hat{p}_1$  and  $\hat{p}_{01}$  based on the EM algorithms are larger than  $\hat{p}_z$  from zheng et al. [14] for some cases, the RMSEs of  $\hat{p}_1$  and  $\hat{p}_{01}$  are smaller than  $\hat{p}_z$  for all the simulation settings. In addition, the population stratification model indeed causes excess homozygosity, which is consistent with Overall and Nichols [24]. The mean  $\hat{p}$  values ( $\hat{p}_1$  and  $\hat{p}_{01}$ )



**Table 6. Simulated size/powers (in %) of LRT<sub>0</sub>, LRT<sub>0b</sub>, LRT<sub>1</sub>, LRT<sub>1b</sub>, LRT<sub>2</sub>, LRT<sub>2b</sub>, Z<sub>0</sub>, Z<sub>1</sub> and Z<sub>2</sub> based on 10000 Monte Carlo replications and 1000 bootstrap replications under X chromosome inactivation and dose compensation, having  $p_m = 0.3$  and the ratio  $N_m : N_f = 1 : 1$ .**

N	$\rho$	$p_f$	LRT <sub>0</sub>	LRT <sub>0b</sub>	LRT <sub>1</sub>	LRT <sub>1b</sub>	LRT <sub>2</sub>	LRT <sub>2b</sub>	Z <sub>0</sub>	Z <sub>1</sub>	Z <sub>2</sub>
800	0.00	0.30	6.5	5.0	10.6	4.9	2.3	5.2	4.8	4.8	4.9
	0.05	0.30	17.2	13.3	10.8	4.9	16.2	25.9	13.0	5.0	17.0
	0.10	0.30	44.1	38.5	11.4	5.2	49.3	63.0	41.2	5.3	50.5
	0.00	0.34	31.7	27.3	42.2	29.2	2.5	5.4	23.5	29.7	5.2
	0.05	0.34	41.8	36.5	41.2	27.9	15.8	26.3	31.6	28.4	16.4
	0.10	0.34	65.1	59.5	41.0	28.2	50.9	64.0	58.5	28.5	52.0
	0.00	0.35	43.6	38.7	55.5	41.3	2.2	4.9	33.6	41.9	5.0
	0.05	0.35	54.3	48.9	55.3	41.5	15.8	26.0	42.0	41.9	16.7
	0.10	0.35	72.1	67.3	53.7	40.2	49.9	63.1	64.8	40.6	50.9
1200	0.00	0.30	6.7	4.8	10.9	5.1	2.2	4.8	5.1	5.0	5.5
	0.05	0.30	22.4	18.0	10.8	5.1	23.0	34.3	18.4	5.0	24.3
	0.10	0.30	60.9	54.8	11.2	5.5	67.3	78.5	58.6	5.5	68.3
	0.00	0.34	42.7	37.8	55.0	40.7	2.2	4.9	32.5	41.3	4.9
	0.05	0.34	57.3	52.1	54.4	40.8	22.1	33.6	46.6	41.0	22.9
	0.10	0.34	81.0	76.8	53.0	39.3	67.5	79.3	76.0	39.5	68.7
	0.00	0.35	59.5	53.8	70.6	57.4	2.3	4.9	47.5	57.9	5.0
	0.05	0.35	71.2	66.2	70.3	57.5	22.7	34.3	59.7	57.8	23.8
	0.10	0.35	88.1	84.7	68.5	55.4	67.7	78.8	83.6	56.0	68.7

doi:10.1371/journal.pone.0145032.t006

using the EM algorithm are a little larger than  $\hat{\rho}_z$  proposed in zheng et al. [14], while  $\hat{\rho}_1$  and  $\hat{\rho}_{01}$  have less standard deviation.

Note that  $\rho = 0$  and  $\rho > 0$  in the null and alternative hypotheses of the likelihood ratio test LRT<sub>0</sub> or LRT<sub>2</sub>, respectively, which causes the “boundary” problem and that the corresponding likelihood ratio test is not expected to follow a  $\chi^2$  distribution [31, 33]. This may be the reason why the size of LRT<sub>0</sub> and LRT<sub>2</sub> is too conservative. Therefore, we use parametric bootstrap techniques to obtain the exact distributions of LRT<sub>0</sub> and LRT<sub>2</sub> in this article.

Due to the presence of the X chromosome inactivation (XCI) and dosage compensation (DC), association analysis and excess homozygosity tests on X chromosome are more complicated than those on autosomes [34]. In the presence of XCI, only one allele from a pair of alleles in females is expressed [35]. Consequently, if considering a locus with two alleles  $M_1$  and  $M_2$ , the effect of the  $M_1$  allele in males should be equivalent to the difference between  $M_2M_2$  and  $M_1M_1$  homozygous females. As such, when we conduct analyses based on allele-counting, we must either count each allele twice in males or equivalently count each allele in females as 0.5, reflecting a “dosage compensation” for X inactivation [34]. It should be noted that LRT<sub>2</sub>, LRT<sub>2b</sub> and Z<sub>2</sub> for  $H_{02} : \rho = 0$  are not affected by XCI and DC because they only use female individuals in the collected sample. Similarly, Z<sub>1</sub> for  $H_{01} : p_m = p_f$  is also not influenced by XCI and DC because it estimates the allele frequencies and the corresponding variances in males and females, respectively. Thus,  $Z_0 = Z_1 + Z_2$  is still valid when XCI and DC exist. To investigate the effect of XCI and DC on LRT<sub>0</sub>, LRT<sub>0b</sub>, LRT<sub>1</sub> and LRT<sub>1b</sub>, where LRT<sub>1b</sub> is the bootstrap version of LRT<sub>1</sub>, we carry out simulation study under several simulation settings in the presence of XCI and DC. The simulation settings and simulation results are listed in Table 6. It is shown in the table that the size of LRT<sub>2b</sub>, Z<sub>0</sub>, Z<sub>1</sub> and Z<sub>2</sub> stays close to the nominal 5% level and the size of LRT<sub>2</sub> is still conservative. However, LRT<sub>0</sub> and LRT<sub>1</sub> without bootstrap cannot control the size well. Fortunately, the type I error rates of LRT<sub>0b</sub> and LRT<sub>1b</sub> with bootstrap are very close to 5%. Furthermore, LRT<sub>0b</sub> is more powerful than Z<sub>0</sub> almost for all the cases and LRT<sub>1b</sub> and Z<sub>1</sub> almost

have the same performance in power. Therefore, in the presence of XCI and DC,  $LRT_{0b}$ ,  $Z_1$  and  $LRT_{2b}$  are recommended. Finally,  $LRT_{0b}$  and  $LRT_{2b}$  can deal with samples of small size. However,  $LRT_{0b}$  and  $LRT_{2b}$  are based on the parametric bootstrap techniques, which are more computationally intensive.

## Supporting Information

**S1 File. Supporting Information.** Tables A–J, root mean squared errors (RMSE) and biases of estimates of  $p_m$ ,  $p_f$  and  $\rho$  based on EM algorithm and zheng et al. [14] under different simulation settings. Tables K–M,  $LRT_0$ ,  $LRT_{0b}$ ,  $Z_0$ ,  $LRT_1$ ,  $Z_1$ ,  $LRT_2$ ,  $LRT_{2b}$ , and  $Z_2$  results of application to rheumatoid arthritis data, respectively. Figs A–L, simulated size/powers of  $LRT_0$ ,  $LRT_{0b}$ ,  $LRT_1$ ,  $LRT_2$ ,  $LRT_{2b}$ ,  $Z_0$ ,  $Z_1$  and  $Z_2$  against  $r = N_m : N_f$  based on 10000 replicates under different simulation settings.  
(PDF)

## Author Contributions

Conceived and designed the experiments: XPY JYZ. Performed the experiments: XPY JYZ. Analyzed the data: XPY QLZ JLL. Contributed reagents/materials/analysis tools: XPY QLZ JLL JYZ. Wrote the paper: XPY JYZ.

## References

1. Horvath S, Xu X, Laird NM. The family based association test method: strategies for studying general genotype–phenotype associations. *Eur J Hum Genet.* 2001; 9: 301–306. doi: [10.1038/sj.ejhg.5200625](https://doi.org/10.1038/sj.ejhg.5200625) PMID: [11313775](https://pubmed.ncbi.nlm.nih.gov/11313775/)
2. Lenart BA, Neviaser AS, Lyman S, Chang CC, Edobor-Osula F, Steele B, et al. Association of low-energy femoral fractures with prolonged bisphosphonate use: a case control study. *Osteoporosis Int.* 2009; 20: 1353–1362. doi: [10.1007/s00198-008-0805-x](https://doi.org/10.1007/s00198-008-0805-x)
3. Reich DE, Goldstein DB. Detecting association in a case-control study while correcting for population stratification. *Genet Epidemiol.* 2001; 20: 4–16. doi: [10.1002/1098-2272\(200101\)20:1%3C4::AID-GEPI2%3E3.0.CO;2-T](https://doi.org/10.1002/1098-2272(200101)20:1%3C4::AID-GEPI2%3E3.0.CO;2-T) PMID: [11119293](https://pubmed.ncbi.nlm.nih.gov/11119293/)
4. Samani NJ, Erdmann J, Hall AS, Hengstenberg C, Mangino M, Mayer B, et al. Genome wide association analysis of coronary artery disease. *N Engl J Med.* 2007; 357: 443–453. doi: [10.1056/NEJMoa072366](https://doi.org/10.1056/NEJMoa072366) PMID: [17634449](https://pubmed.ncbi.nlm.nih.gov/17634449/)
5. Voight BF, Scott LJ, Steinthorsdottir V, Morris AP, Dina C, Welch RP, et al. Twelve type 2 diabetes susceptibility loci identified through large-scale association analysis. *Nat Genet.* 2010; 42: 579–589. doi: [10.1038/ng.609](https://doi.org/10.1038/ng.609) PMID: [20581827](https://pubmed.ncbi.nlm.nih.gov/20581827/)
6. Wang M, Lin S. FamLBLE: detecting rare haplotype disease association based on common SNPs using case-parent triads. *Bioinformatics.* 2014; 30: 2611–2618. doi: [10.1093/bioinformatics/btu347](https://doi.org/10.1093/bioinformatics/btu347) PMID: [24849576](https://pubmed.ncbi.nlm.nih.gov/24849576/)
7. Weedon MN, Lango H, Lindgren CM, Wallace C, Evans DM, Mangino M, et al. Genome-wide association analysis identifies 20 loci that influence adult height. *Nat Genet.* 2008; 40: 575–583. doi: [10.1038/ng.121](https://doi.org/10.1038/ng.121) PMID: [18391952](https://pubmed.ncbi.nlm.nih.gov/18391952/)
8. Zhang H, Wheeler W, Wang Z, Taylor PR, Yu K. A fast and powerful tree-based association test for detecting complex joint effects in case-control studies. *Bioinformatics.* 2014; 30: 2171–2178. doi: [10.1093/bioinformatics/btu186](https://doi.org/10.1093/bioinformatics/btu186) PMID: [24794927](https://pubmed.ncbi.nlm.nih.gov/24794927/)
9. Schaid DJ, Jacobsen SJ. Biased tests of association: comparisons of allele frequencies when departing from Hardy-Weinberg proportions. *Am J Epidemiol.* 1999; 149: 706–711. doi: [10.1093/oxfordjournals.aje.a009878](https://doi.org/10.1093/oxfordjournals.aje.a009878) PMID: [10206619](https://pubmed.ncbi.nlm.nih.gov/10206619/)
10. Chung RH, Morris RW, Zhang L, Li YJ, and Martin RR. X-APL: an improved family-based test of association in the presence of linkage for the X chromosome. *Am J Hum Genet.* 2007; 80: 59–68. doi: [10.1086/510630](https://doi.org/10.1086/510630) PMID: [17160894](https://pubmed.ncbi.nlm.nih.gov/17160894/)
11. Ding J, Lin S, Liu Y. Monte Carlo pedigree disequilibrium test for markers on the X chromosome. *Am J Hum Genet.* 2006; 79: 567–573. doi: [10.1086/507609](https://doi.org/10.1086/507609) PMID: [16909396](https://pubmed.ncbi.nlm.nih.gov/16909396/)

12. Horvath S, Laird NM, Knapp M. The transmission/disequilibrium test and parental-genotype reconstruction for X-chromosomal markers. *Am J Hum Genet.* 2000; 66: 1161–1167. doi: [10.1086/302823](https://doi.org/10.1086/302823) PMID: [10712229](https://pubmed.ncbi.nlm.nih.gov/10712229/)
13. Zhang L, Martin ER, Chung RH, Li YJ, Morris RW. X-LRT: a likelihood approach to estimate genetic risks and test association with X-linked markers using a case-parents design. *Genet Epidemiol.* 2008; 32: 370–380. doi: [10.1002/gepi.20311](https://doi.org/10.1002/gepi.20311) PMID: [18278816](https://pubmed.ncbi.nlm.nih.gov/18278816/)
14. Zheng G, Joo J, Zhang C, Geller NL. Testing association for markers on the X chromosome. *Genet Epidemiol.* 2007; 31: 834–843. doi: [10.1002/gepi.20244](https://doi.org/10.1002/gepi.20244) PMID: [17549761](https://pubmed.ncbi.nlm.nih.gov/17549761/)
15. Clayton D. Testing for association on the X chromosome. *Biostat.* 2008; 9: 593–600. doi: [10.1093/biostatistics/kxn007](https://doi.org/10.1093/biostatistics/kxn007)
16. Hickey PF, Bahlo M. X chromosome association testing in genome wide association studies. *Genet Epidemiol.* 2011; 35: 664–670. doi: [10.1002/gepi.20616](https://doi.org/10.1002/gepi.20616) PMID: [21818774](https://pubmed.ncbi.nlm.nih.gov/21818774/)
17. Chen Z, Ng HKT, Li J, Liu Q, Huang H. Detecting associated single-nucleotide polymorphisms on the X chromosome in case control genome-wide association studies. *Stat Methods Med Res.* 2014; doi: [10.1177/0962280214551815](https://doi.org/10.1177/0962280214551815)
18. Li CC. *First Course in Population Genetics.* Boxwood Press; 1976.
19. Gillespie JH. *Population Genetics: A Concise Guide.* 1st ed. Johns Hopkins University Press; 2010.
20. König IR, Loley C, Erdmann J, Ziegler A. How to include chromosome X in your genome-wide association study. *Genet Epidemiol.* 2014; 38: 97–103. doi: [10.1002/gepi.21782](https://doi.org/10.1002/gepi.21782)
21. Chang D, Gao F, Slavney A, Ma L, Waldman YY, Sams AJ, et al. Accounting for eXentricities: analysis of the X chromosome in GWAS reveals X-linked genes implicated in autoimmune diseases. *PLoS ONE.* 2014; 9: e113684. doi: [10.1371/journal.pone.0113684](https://doi.org/10.1371/journal.pone.0113684) PMID: [25479423](https://pubmed.ncbi.nlm.nih.gov/25479423/)
22. Wright S. *Systems of mating.* *Genetics.* 1921; 6: 111–178. PMID: [17245958](https://pubmed.ncbi.nlm.nih.gov/17245958/)
23. Nei M. *Molecular evolutionary genetics.* Columbia University Press, New York; 1987.
24. Overall ADJ, Nichols RA. A method for distinguishing consanguinity and population substructure using multilocus genotype data. *Mol Biol Evol.* 2001; 18: 2048–2056. doi: [10.1093/oxfordjournals.molbev.a003746](https://doi.org/10.1093/oxfordjournals.molbev.a003746) PMID: [11606701](https://pubmed.ncbi.nlm.nih.gov/11606701/)
25. Brookfield JFY. A simple new method for estimating null allele frequency from heterozygote deficiency. *Mol Ecol.* 1996; 5: 453–455. PMID: [8688964](https://pubmed.ncbi.nlm.nih.gov/8688964/)
26. Dempster AP, Laird NM, Rubin DB. Maximum likelihood from incomplete data via the EM algorithm. *J R Stat Soc B.* 1977; 39: 1–38.
27. Mao WG, He HQ, Xu Y, Chen PY, Zhou JY. Powerful haplotype-based Hardy-Weinberg equilibrium tests for tightly linked loci. *PLoS ONE.* 2013; 8: e77399. doi: [10.1371/journal.pone.0077399](https://doi.org/10.1371/journal.pone.0077399) PMID: [24167573](https://pubmed.ncbi.nlm.nih.gov/24167573/)
28. Emigh TH. A comparison of tests for Hardy-Weinberg equilibrium. *Biometrics.* 1980; 36: 627–642. doi: [10.2307/2556115](https://doi.org/10.2307/2556115) PMID: [25856832](https://pubmed.ncbi.nlm.nih.gov/25856832/)
29. Kuk AYC, Zhang H, Yang Y. Computationally feasible estimation of haplotype frequencies from pooled DNA with and without Hardy-Weinberg equilibrium. *Bioinformatics.* 2009; 25: 379–386. doi: [10.1093/bioinformatics/btn623](https://doi.org/10.1093/bioinformatics/btn623) PMID: [19050036](https://pubmed.ncbi.nlm.nih.gov/19050036/)
30. Gartler SM. A brief history of dosage compensation. *J Genet.* 2014; 93: 591–595. doi: [10.1007/s12041-014-0360-5](https://doi.org/10.1007/s12041-014-0360-5) PMID: [25189265](https://pubmed.ncbi.nlm.nih.gov/25189265/)
31. Weir BS, Cockerham CC. *Complete Characterization of Disequilibrium at Two Loci.* *Mathematical Evolutionary Theory,* Princeton University Press; 1989.
32. Self SG, Liang KY. Asymptotic properties of maximum likelihood estimators and likelihood ratio tests under nonstandard conditions. *J Am Stat Assoc.* 1987; 82: 605–610. doi: [10.1080/01621459.1987.10478472](https://doi.org/10.1080/01621459.1987.10478472)
33. Zhang DW, Lin XH. Hypothesis testing in semiparametric additive mixed models. *Biostat.* 2003; 4: 57–74. doi: [10.1093/biostatistics/4.1.57](https://doi.org/10.1093/biostatistics/4.1.57)
34. Bielawski JP, Yang Z. *Maximum Likelihood Methods for Detecting Adaptive Protein Evolution.* *Statistical Methods in Molecular Evolution.* Springer; 2005.
35. Clayton DG. Sex chromosomes and genetic association studies. *Genome Med.* 2009; 1: 110. doi: [10.1186/gm110](https://doi.org/10.1186/gm110) PMID: [19939292](https://pubmed.ncbi.nlm.nih.gov/19939292/)
36. Amos-Landgraf JM, Cottle A, Plenge RM, Friez M, Schwartz CE, Longshore J, et al. X chromosome-inactivation patterns in 1,005 phenotypically unaffected females. *Am J Hum Genet.* 2006; 79: 493–499. doi: [10.1086/507565](https://doi.org/10.1086/507565) PMID: [16909387](https://pubmed.ncbi.nlm.nih.gov/16909387/)