

# A Master Plan 1.5 Using Optical Scan Counters: An Analysis of the 2012 Presidential Election Data in South Korea

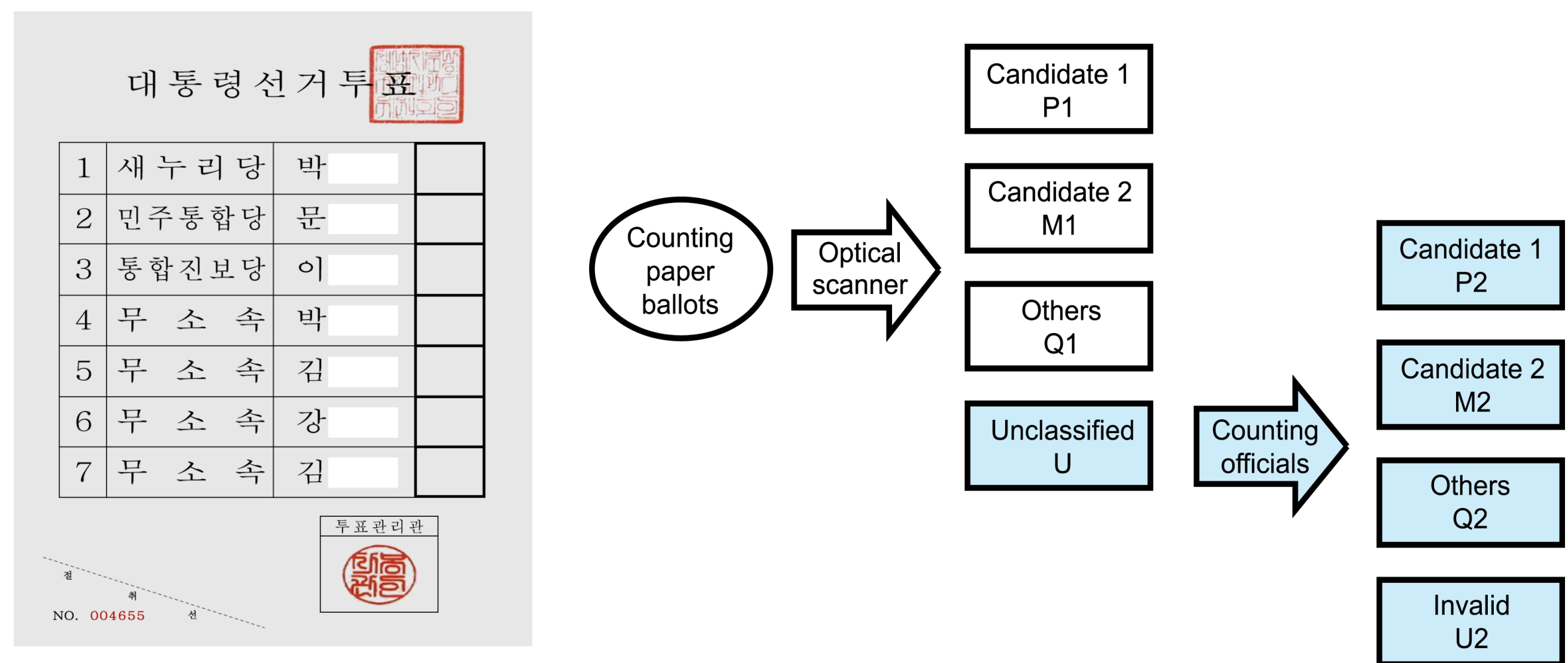
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## Abstract

- ❖ Optical scan counters in election have been used to count votes, sorting them into classified and unclassified ballots. The unclassified ballots are manually counted by electoral officials.
- ❖ We propose a measure  $K$ , to test between-candidate relative inequality whose valid ballots are unclassified by the optical counters. We prove  $E[K]=1$  and  $\text{Var}(K)$  depends on electoral district size and unclassified rate.
- ❖ The 2012 presidential election in South Korea was a close election with 52% vs 48% for the top two candidates.
- ❖ We found  $K=1.5$  nationally, which indicates a **strong discrepancy** between *machine counted* and *human counted* ballots.
- ❖ Both **systematic unintentional bias** and **intentional manipulation** were considered to explain this. Simulation results from the latter scenario with rigged optical counters are quite close to actual vote results, suggesting the election might have been affected by a national manipulation as optical counters are vulnerable programmable devices.
- ❖ The proposed statistical methods for  $K$  contribute to securing accurate vote counting in elections worldwide where the optical counters are used.

## Background: Votes Sorting Process: Classified versus Unclassified



## Motivation Example

Voting results for three specific districts from three presidential elections in 2002, 2007, 2012

Election year and district	Votes from the classified (sorted by op-scanners)		Votes from the unclassified (sorted by counting officials)		$K=K_U/K_C$
	candidate 1 ( $P_C$ ) <sup>a</sup>	candidate 2 ( $M_C$ ) <sup>a</sup>	candidate 1 ( $P_U$ ) <sup>b</sup>	candidate 2 ( $M_U$ ) <sup>b</sup>	
16 <sup>th</sup> in 2002, district G	36.3%	56.5%	33.7%	50.3%	1.04
17 <sup>th</sup> in 2007, district N	23.1%	47.7%	25.1%	50.7%	1.02
district Y	16.9%	59.6%	17.5%	59.4%	1.04
18 <sup>th</sup> in 2012, district G	40.2%	59.4%	39.9%	43.7%	1.35
district N	46.3%	53.3%	45.0%	36.0%	1.44
district Y	51.9%	47.8%	54.4%	36.6%	1.37

<sup>a</sup>  $P_C$  = (votes for candidate 1/total votes);  $M_C$  = (votes for candidate 2/total votes) from classified

<sup>b</sup>  $P_U$  = (candidate 1/total votes);  $M_U$  = (candidate 2/total votes) from unclassified;  $K_U = P_U/M_U$

## A Proposed Measure for Between-Candidate Relative Inequality

$K=K_U/K_C = (P2/M2)/(P1/M1)$  for any electoral district.

- P1 & M1: votes counts from the classified votes
- P2 & M2: votes counts from the unclassified votes

• **Known fact:**  $X \sim B(n, p)$ ,  $E\left[\frac{1}{X+1}\right] = \frac{1}{(n+1)p} \approx \frac{1}{np}$  for large  $n$

• **Theoretical expectation of  $K$ :**  $E[K]=1$

$$E[K] = E\left[\frac{P2/M2}{P1/M1}\right] = E\left[\frac{P2}{P1}\right] \cdot E\left[\frac{M1}{M2}\right] = \frac{r \cdot (1-r)}{(1-r) \cdot r} = 1$$

$P1 \sim B(P, 1-r)$ ,  $P2 \sim B(P, r)$ , where  $P1+P2=P$  fixed.

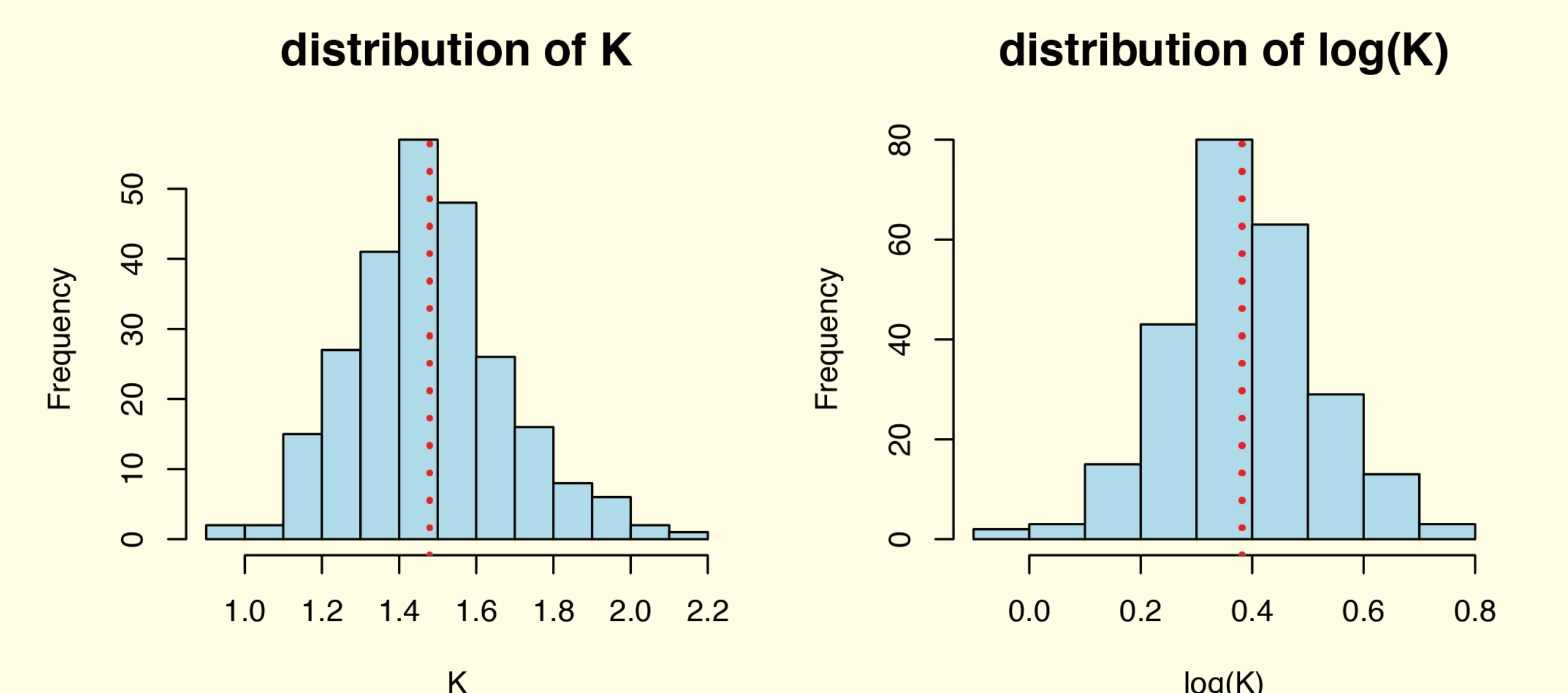
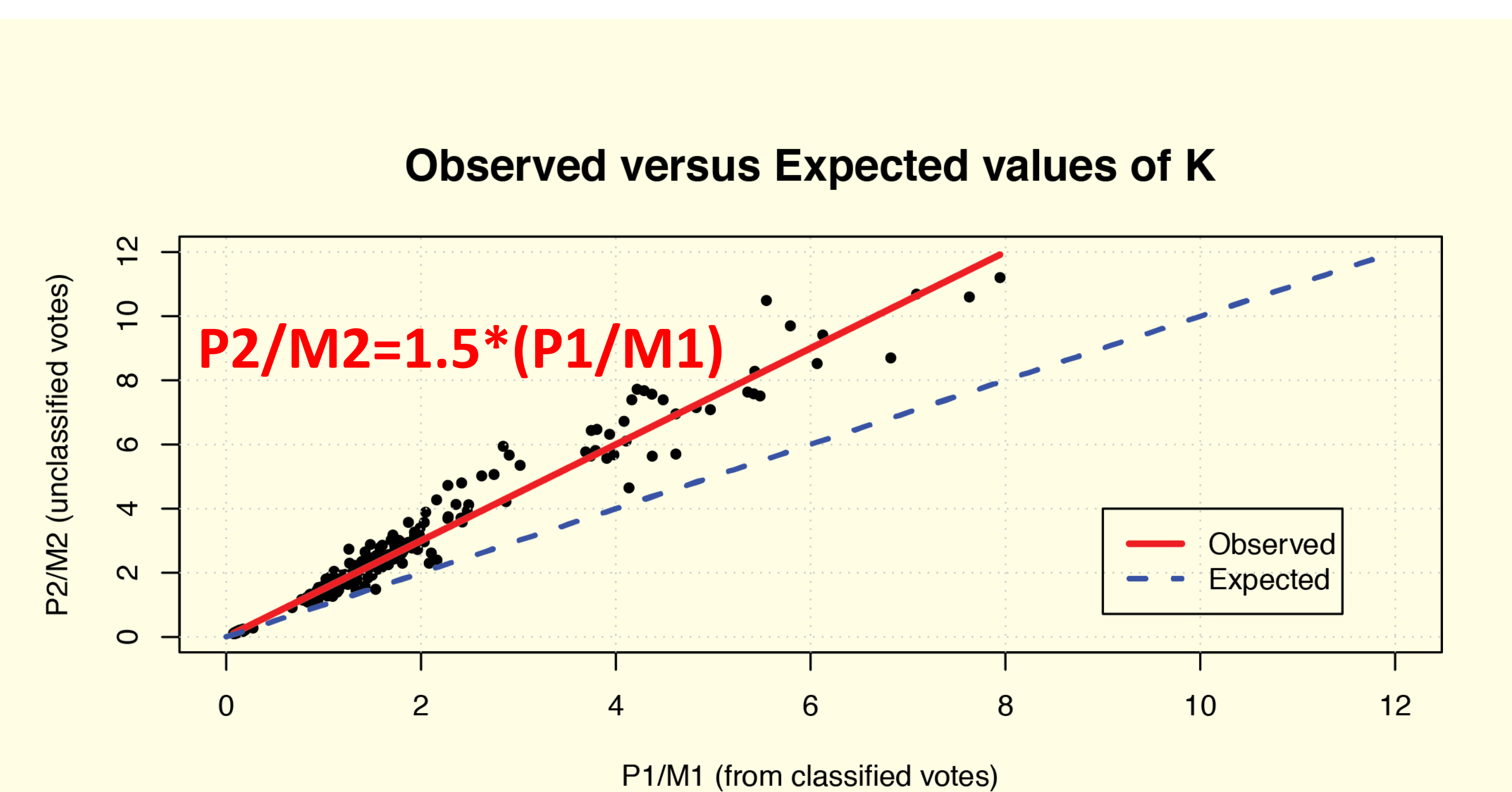
$M1 \sim B(M, 1-r)$ ,  $M2 \sim B(M, r)$ , where  $M1+M2=M$  fixed.

$r = \text{Pr}(U_M) = \text{Pr}(U_p)$ , rate of the unclassified votes

• **Variance of  $K$  depending on electoral district size and  $r$**

$$\text{Var}(K) \cong \frac{(P+M)r(1-r)+1}{PMr(1-r)^2} \cong \frac{(P+M)}{PMr(1-r)}$$

## National Model: $K=1.5$ (Linear Regression with $R^2=0.98$ )

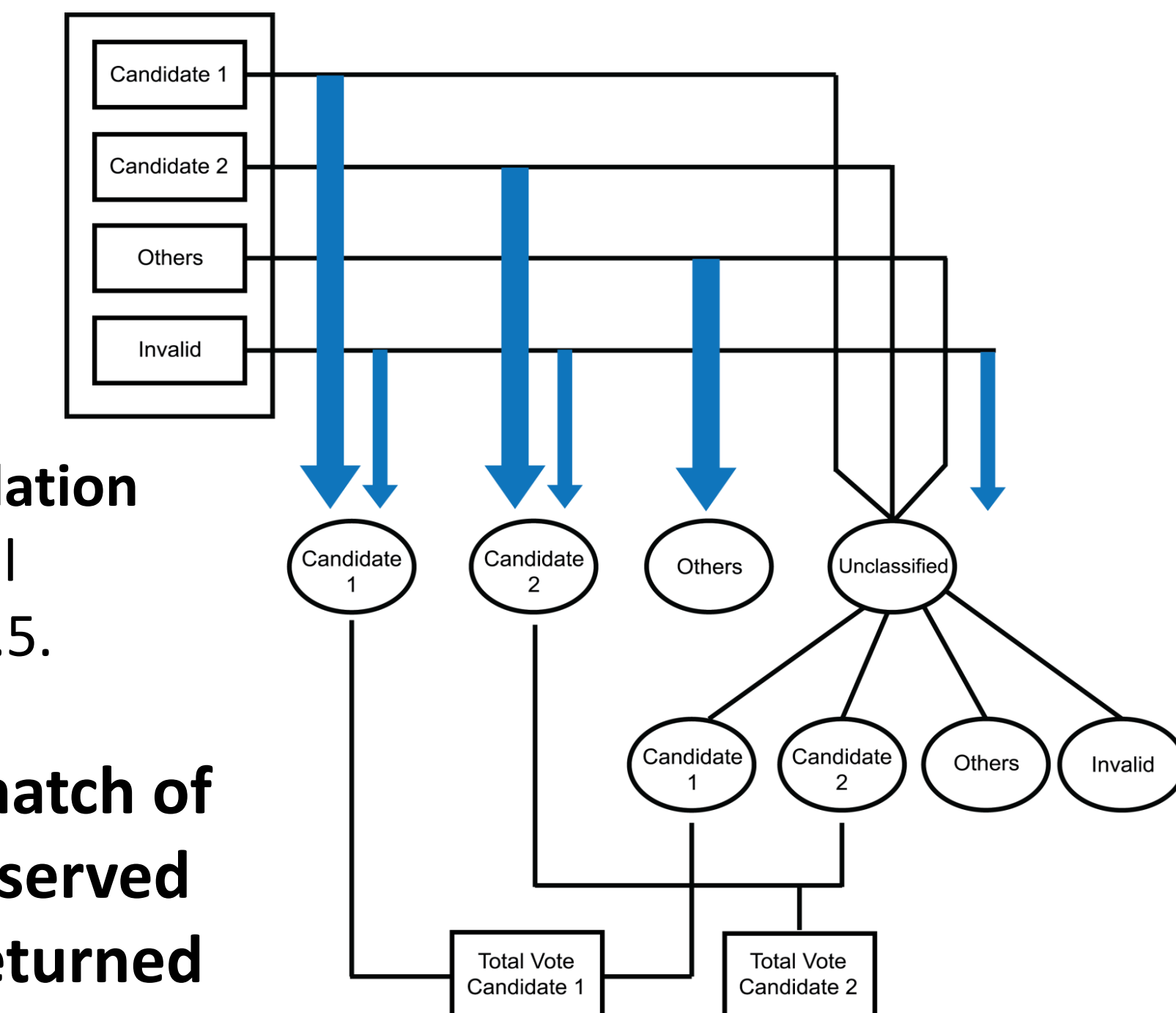


## Simulations with Two Scenarios

➤ **Scenario 1: unintentional systematic bias**  
Assume a consistent op-scan performance across the country:  
 $P2 \sim B(P, r+\beta)$ , where  $M2 \sim B(M, r)$ .

➤ **Scenario 2: intentional systematic manipulation**  
Apply conditional Bernoulli and multinomial distributions to sorting algorithm with  $K=1.5$ .

➔ **Scenario 1 resulted in an overall mismatch of the variability of unclassified rates observed at district level, whereas scenario 2 returned comparable results to the actual election outcomes at both district and national levels.**



Simulation Process (Scenario 2)

## Results: Actual vs. Simulated Votes

251 districts combined	Total number of votes	Total unclassified votes	Votes from the classified		Votes from the unclassified		Invalid votes
			candidate 1	candidate 2	candidate 1	candidate 2	
Actual	29,827,252	1,111,165	14,782,150	13,828,239	586,632	397,505	112,360
Simulated 1	29,827,252	1,229,495	14,683,046	13,797,770	685,822	427,442	112,570
Simulated 2	29,827,252	1,080,700	14,787,440	13,857,352	594,739	370,907	111,117

## Merits of the Relative Ratio $K$

- ❖ The proposed method can be more effective than auditing when the op-scan counters are used.
- ❖ The  $K$ -value can be examined for some electoral districts individually for local, regional, or national levels.
- ❖ Easy and economic for time and cost required

## Discussions on Op-scanners and Fair Election

- ❖ This study demonstrates a potential serious loophole in using the op-scan counters, which can be **error-free but not manipulation-free**
- ❖ Op-scan counters can generate serious misclassifications **by a pre-programmed algorithm**, not by random mechanical malfunctions.
- ❖ Serious errors can go undetected if results are not audited effectively, resulting in election winner change.

## ➔ Solutions for detecting election frauds:

- ✓ Auditing a well curated paper trail against the electronic results or a random sample of the ballot boxes
- ✓ The proposed measure ( $K$ ) to detect between candidate relative inequality