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Commentary on: Thompson WC, Taroni F, Aitken CGG. How the probability of a false positive affects the value of DNA evidence. J Forensic Sci 2003;48(1):47–54.

Sir:

Thompson et al. (1) makes an interesting contribution to the literature of errors and DNA identification. Their essential and novel point is that even a small possibility of error may become important in those situations—namely a databank search or a dragnet—for which the prior odds for guilt of the matching suspect are very small. In effect, they note that the small prior odds have a (inverse) multiplier effect on the false positive probability. A false positive error rate that would be tolerable for suspect casework might therefore be intolerable, they argue, for "suspectless" cases (i.e., cases with no particularly suspicious suspect, where really there are thousands of suspects). Indeed, if the numbers that they use as examples are realistic, their argument would seem to spell doom for catching criminals through DNA databanks or dragnets.

Some may see a threat. We see opportunity. The reasoning advanced in (1) can be turned around and thereby give a possibly useful upper bound on the actual rate of false positives by taking advantage of the aforementioned multiplier effect. In brief, according to the example scenarios, dragnet and databank searches must quite often nab the wrong person. If to the contrary databank searches do not often nab innocent suspects, this contradiction would prove that the examples are unrealistic and that false positive errors occur at less than the speculated rate. For example, consider a dragnet with about 1000 suspects, so the prior odds for each is about 1:1000, random match odds 10^{-9} (which might as well be zero) and false positive probability $F = 10^{-4}$—one of the hypothetical situations of Table 1 in (1). The posterior odds are then merely 10:1, which means that in $\frac{1}{11}$ of such cases the wrong suspect has been identified. The arithmetic for a databank hit is even more alarming, as the universe of plausible suspects may be larger. If for example the 100,000 profiles in the California DOJ databank are deemed to be suspects, again taking the approximation that the random matching odds are zero, and supposing $F = 10^{-4}$, the posterior odds that a cold hit catches the real culprit would be a miniscule 1:10—10 of every 11 hits are spurious! Can this be true?

There are ways to assess whether so dire a prediction is realistic. If even $\frac{1}{11}$ of identified suspects are random misidentifications, then follow-up investigation should crumble in many of these cases. In California and many jurisdictions, a case may not be prosecuted based on a databank hit alone. Therefore the mere fact of conviction provides some argument that follow-up investigations are availing. Unfortunately, though, there are no records or statistics about what happens to databank hit cases. Investigators normally regard a databank hit as a tip, not a command, and do not routinely and systematically provide feedback as to the success of hits. A skeptic could plausibly believe that investigators hit a blind alley $\frac{1}{11}$ of the time and quietly drop the cases. A study could be done, but we admit it would not be easy.

One kind of blind alley, though, is special. If the suspect was incarcerated at the time of the offense—a powerful alibi—we expect that fact to come to light. Obviously, a substantial percentage of the people in a convicted offender databank, which is where cold hits come from, are repeat offenders and will be in jail at any given time. If false positive errors occur, they should randomly identify innocent suspects independently of whether the innocent suspect is in jail. Therefore, assuming the example numbers suggested in (1), a predictable and significant proportion of databank hits should be disproved by prison records. We know of one such complaint (Dave Coffman, personal communication). The Florida Department of Law Enforcement has recorded about 980 cold hits. On one of them, a rape case, the investigator complained to the lab the suspect was in jail at the time of the offense. The reported match was not wrong—the suspect had an identical twin. This anecdote supports the thesis that prison alibis, if they existed, would be made known to the DNA laboratory. Common sense also supports it: an investigator who obtains the definite contradictory evidence of a prison alibi has something worth reporting back, as opposed to his vague situation when he merely fails to find confirmation. In any case, prison records can be systematically searched, either as a retrospective study to assess past databank hits, or it could be implemented as an automatic control to be checked for every hit in the future. Indeed, in California such an automatic control has been in place since the beginning of the databank. Of over 300 cold hits, none have been to inmates incarcerated at the time of the offense.

The false positive rates that are speculated in (1) are essentially citation of previous speculation; by comparison even off-the-cuff estimates based on our "prison alibi" reasoning might rate as sound. To that end, we estimate that $\frac{2}{3}$ of those in convicted offender databanks are repeat offenders, so a plausible guess is that 30% of the total are in prison at any given time. Therefore of erroneous cold hits, 30% should be contradicted by a prison alibi. California has had $C = 300$ cold hits to date, of which CF/P, $F =$ false positive rate and $P =$ prior odds, would be expected to be erroneous and $0.3CF/P$ contradictable by prison alibi. The observed value of $0.3CF/P$ is zero. Considering a 95% upper confidence estimate, probably therefore $0.3CF/P < 3$, or $F < 10P/C$. Taking $P = 10^{-3}$ as in (1), $F < 1/30000$. P may also be 10 or 100 times smaller, and worldwide C may be 10 or more times larger, suggesting $F < 1/10{,}000{,}000$. Of course these are crude estimates, and restricted by the limitations of statistics are merely upper bounds. Augmenting statistics by common sense some will argue that since convicted offender samples are catalogued by a contracting laboratory normally unrelated to the lab where the crime stain is analyzed, contamination or sample mix-up is unimaginable. In a dragnet situation, the crime stain is typed before the suspects are typed, and again $F > 0$ seems unimaginable. Imaginations vary though, so even our crudely estimated numerical upper bounds as to the rate at which the "impossible" happens might aid communication and insight.

The "confidence estimate" approach we used above is one that has sometimes been used (e.g., by the defense) to make the point that even a spotless record over 100 or 1000 cases provides—using a merely statistical analysis—less than certainty "beyond a reasonable doubt" against the possibility of error in the instant case. The "multiplier effect" we have referred to comes about because each of the many suspects in a dragnet or a databank is a separate opportunity for error, so the spotless record (if such it be) is effectively over five or so orders of magnitude more trials.

Naturally, the analysis we have presented is specific to the suspectless scenario. Suspect cases are often quite different and our comments might have no bearing. To the extent, though, that the circumstances of evidence collection and analysis in a suspect case may be similar to the suspectless circumstances our estimates may be helpful.

References

1. Thompson WC, Taroni F, Aitken CGG. How the probability of a false positive affects the value of DNA evidence. J Forensic Sci 2003;48(1):47–54. [PubMed]

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