FROM FINGERPRINTS TO OPIOIDS: HOW DATA SCIENCE CAN SUPPORT LAW AND PUBLIC POLICY

By: Alan Salzberg, Ph.D.[*] *& Corey West*[**]

TABLE OF CONTENTS

I. INTRODUCTION

Half a century ago, William Fairley and Michael Finkelstein suggested a statistical methodology for sorting evidence introduced by experts.[1] Contrary to what courts have sometimes suggested, Finkelstein and Fairley stated that providing a statistical probability tends to weaken the strength of expert testimony and help the jury weigh such evidence.[2]

Laurence Tribe, the now well-known legal scholar, responded by arguing against the use of statistics in the courtroom in "Trial by Mathematics: Precision and Ritual in the Legal Process."[3] Tribe feared "the problem of the overpowering number, that one hard piece of information, is that it may dwarf all efforts to put it into perspective with more impressionistic sorts of evidence."[4] Tribe felt that the use of statistics in court could "shift the focus away from such elements as volition, knowledge, and intent, and toward such elements as identity and occurrence[.] . . ."[5] Thus, in light of uncertainty, Tribe would allow the expert to opine, but cautions against allowing the jury to hear a quantification of the chances of an exact match.[6]

At the time of the Finkelstein-Fairley and Tribe articles, there was little hope of identifying the statistics around events that were less likely than one in a few hundred because of the limit of studies that involve manual review. However, with the rise of data science and the increased availability of large databases, information is introduced in both criminal and civil litigation that could never have been produced manually.

In this article, we explore the implications of quantification of evidence in criminal and civil litigation, as well as in public policy. We will work through two examples in order to demonstrate the mathematics. The first is an international crime in which a single latent fingerprint is found. The second is a nationwide crisis in which we use and employ multiple databases to illustrate the complexity of the problem. What was once speculation can now be quantified, and as we will see, what was once considered a certainty, can now be questioned.

---

[*] Alan Salzberg is a Principal and Senior Statistician at Salt Hill Statistical Consulting.
[**] Corey West is a Senior Manager and Statistician at Summit Consulting, LLC.
[1] *See generally* Michael O. Finkelstein & William B. Fairley, *A Bayesian Approach to Identification Evidence*, 83 HARV. L. REV. 489 (1970).
[2] *Id.* at 495–96.
[3] Laurence H. Tribe, *Trial by Mathematics: Precision and Ritual in the Legal Process*, 84 HARV. L. REV. 1329 (1971).
[4] *Id.* at 1360.
[5] *Id.* at 1366.
[6] *Id.* at 1355.

II. 2004 MADRID BOMBINGS

During the morning rush hour of Thursday, March 11, 2004, terrorists set off ten bombs on four commuter trains in Madrid.[7] It was the deadliest terror attack in Spain's history, killing 193 people and injuring more than 2,000.[8] After the attack, the Spanish National Police (SNP) found fingerprints on a bag containing detonators and explosives that was later connected to the bombings.[9] The SNP transmitted these fingerprints to the International Criminal Police Organization (INTERPOL) in the hope of identifying potential suspects. INTERPOL then transmitted the fingerprints to the FBI.[10]

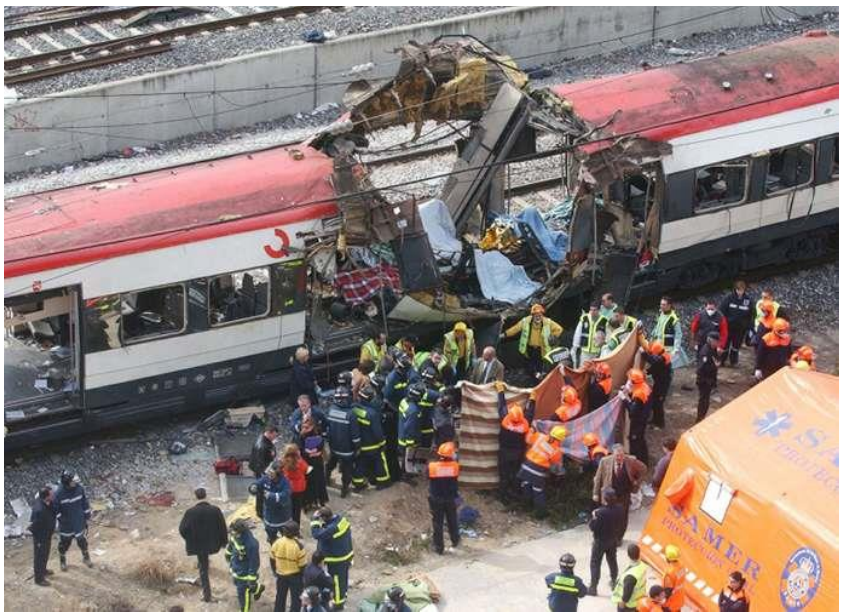

Figure 1: Aftermath of the Madrid Bombings[11]

---

[7] *See, e.g.*, *Spain Train Bombing Fast Facts*, CNN (Feb. 26, 2020, 2:02 PM), https://www.cnn.com/2013/11/04/world/europe/spain-train-bombings-fast-facts/index.html [https://perma.cc/DRJ6-LV8U].

[8] *Terrorists Bomb Trains in Madrid*, HISTORY, https://www.history.com/this-day-in-history/terrorists-bomb-trains-in-madrid [https://perma.cc/9DM5-WSFQ]. While there were thirteen explosive devices, three did not detonate. *Id.*

[9] Robin Mejia et al., *What Does a Match Mean? A Framework for Understanding Forensic Comparisons*, SIGNIFICANCE, Apr. 2019, at 25.

[10] U.S. DEP'T OF JUSTICE, OFF. OF THE INSPECTOR GEN., A REVIEW OF THE FBI'S HANDLING OF THE BRANDON MAYFIELD CASE 29–30 (2006) [hereinafter OIG Report], https://oig.justice.gov/special/s0601/final.pdf [https://perma.cc/UPX2-LSZ6].

[11] Michael Ray, *Madrid Train Bombings of 2004*, BRITANNICA (Mar. 4 2020), https://www.britannica.com/event/Madrid-train-bombings-of-2004 [https://perma.cc/M8B4-KKVP].

Upon receipt of the fingerprints, the FBI began by processing the fingerprints through multiple databases as part of the Integrated Automated Fingerprint Identification System (IAFIS).[12] IAFIS allows for the search of a number of databases, which in total contain the fingerprints of more than forty-seven million people.[13] IAFIS finds and scores up to twenty potential matches, which can then be manually reviewed.[14] On March 16, a reviewer found a match for one of the Madrid fingerprints in the FBI criminal database, which was fourth on the IAFIS list of twenty potential matches.[15] A second reviewer verified the match.[16]

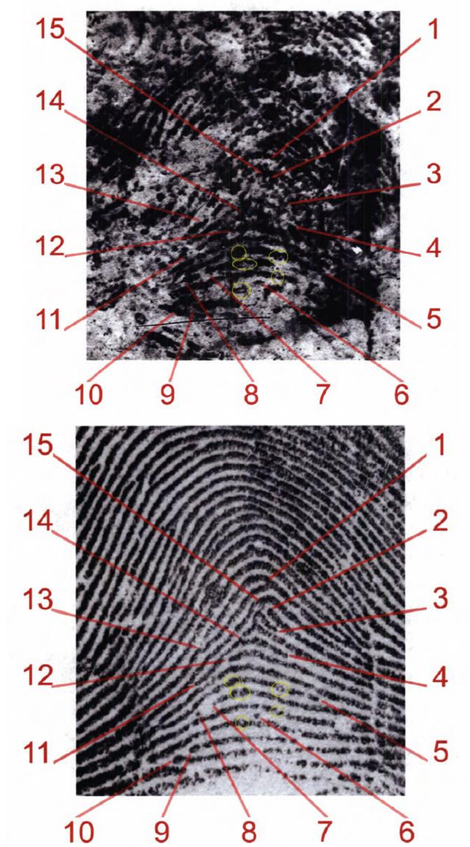

Figure 2: Latent Fingerprint *(top)* Versus Database Matching Fingerprint *(bottom)*[17]

[12] OIG Report, *supra* note 10, at 30.
[13] *Id.*
[14] *Id.* at 30–31.
[15] *Id.* at 31.
[16] Despite this, other reviewers were not sure the fingerprint was a match. *See id.* at 32–33.
[17] *Id.* at 44–45.

Thus, on March 16, only five days after the bombings, the identity of a suspect had been obtained by culling millions of potential fingerprints. The suspect, a lawyer from Oregon, would never have been identified if not for this technology. By March 19, he was under 24-hour FBI surveillance.[18] Soon after, the government obtained authorization for covert searches of his home and office.[19] Surveillance continued until May 6, when the attorney was arrested and held as a material witness.[20]

Data science and technology had won the day—or had it? Before we answer that question, we must explore statistical matching in general and review specific results for fingerprint matching.

III. WHAT DOES A MATCH MEAN?

Imagine we, as investigators, have a piece of identification evidence, and we wish to do a test of whether the evidence "matches" a particular individual. In this example, assume we have a latent fingerprint, and we want to test whether it matches someone in the database. At the outset, there are four possible outcomes for each person the fingerprint is tested against, each of which has a name in statistical terminology:[21]

> True Positive: Our test reports it as a match, and the test is right; it does come from the individual we were trying to match against.
>
> True Negative: Our test reports it as *not* a match, and the test is right; it does *not* come from the individual we were trying to match against.
>
> False Positive: Our test reports it as a match, and the test is wrong; it does *not* come from the individual we were trying to match against.
>
> False Negative: Our test reports it as *not* a match, and the test is wrong; it does come from the individual we were trying to match against.

The four possibilities can be summarized in the table below.

---

[18] OIG Report, *supra* note 10, at 37.
[19] *Id.* at 38–40.
[20] *Id.* at 67.
[21] I am assuming no inconclusive results here, where the test fails to say whether it is or is not a match.

Test Outcome	**Test Reports Match**	**Test Reports Non-Match**
Actual Match	True Positive	False Negative
Actual Non-Match	False Positive	True Negative

Table 1: Statistical Categorization Table

The first column of the table shows the possible results when the test reports a match: we may either have a true positive or a false positive. When the test reports a non-match, we may either have a false negative or a true negative. Thus, while there are two types of errors, only one appears to be relevant once we have a test result.

Now, in an ideal world, we would have a perfect test, and thus it delivers either a true positive or a true negative; the test would never be wrong. Unfortunately, identification evidence of all kinds, even eye-witness testimony, is known to be imperfect.[22] We can quantify that imperfection if we know the false positive rate and the false negative rate. The false positive rate is the percentage of the non-matches the test incorrectly identifies as matches. The false negative rate is the percentage of actual matches the test incorrectly identifies as non-matches. The equations for these rates are expressed as:

$$\text{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives}+\text{True Negatives}}$$

$$\text{False Negative Rate} = \frac{\text{False Negatives}}{\text{True Positives}+\text{False Negatives}}$$

A. *False Positive Rate for Fingerprints*

As shown in the above equation, we can estimate the chances of a false positive by taking the total number of incorrect matches (false positives) divided by the total number of instances tested that were not a match (false positives plus true negatives). Using IAFIS as an example, we will consider the twenty fingerprints matched by IAFIS in the Madrid case and assume there

[22] For a discussion regarding eye-witness testimony, see, e.g., Hal Arkowitz & Scott O. Lilienfeld, *Why Science Tells Us Not to Rely on Eyewitness Accounts*, SCI. AM. (Jan. 1, 2010), https://www.scientificamerican.com/article/do-the-eyes-have-it/ [https://perma.cc/8VLA-PPLJ].

were two million fingerprints in the database.[23]

Assuming one of the twenty is a correct match, there were nineteen false matches, meaning the false positive rate is 19/1,999,999, or only about 1 in 100,000. Therefore, from that perspective, IAFIS looks like an excellent test, rarely giving a false positive. However, this rate is a little deceptive, as IAFIS will never give more than twenty "matches."[24] This means that there may have been hundreds or thousands of close matches but IAFIS will just return the top twenty. Further, there is no guarantee that any of these twenty will be the true match.

The identification in the Madrid bombings ultimately relied on manual fingerprint identification. Fingerprints identified by IAFIS were examined by an expert to determine if any of the fingerprints matched the latent fingerprint. Until recently, there were few, if any, scientific studies on the accuracy of manual fingerprint identifications. The Madrid bombings spurred additional research and now there are a few more scientific evaluations. A recent President's Council of Advisors on Science and Technology Report (PCAST Report) on this subject reported there are now two "appropriately designed . . . studies" meant to validate fingerprint identification.[25] The first study, which first finds close matches using the IAFIS data, gives a false positive rate of 1 in 604 (0.2 percent). A second study gives a much higher 1 in 24 (4.2 percent) false positive rate.[26] Statistical variation implied by the sample sizes means the actual rate indicated by the first study could be as high as 1 in 306 (0.3 percent) and the actual rate indicated by the second study suggests the actual rate could be as high as 1 in 18 (5.4 percent).[27]

B. *False Negative Rate for Fingerprints*

To round out the evaluation of a fingerprint test, the rate of false positives is not enough. The rate of false negatives needs to be known as well. Recall that a false negative occurs when the test indicates the fingerprint does not match when in fact it does. The false negative rate represents the chances a test will fail to identify that a fingerprint matches an individual. By using the

---

[23] While IAFIS can access databases with a total of more than 47 million fingerprints, the size of the criminal database (that provided the twenty potential matches) is not clear from the description in the OIG Report.

[24] OIG Report, *supra* note 10, at 30 (stating that IAFIS generates the "top 10 to 20 highest scoring candidate fingerprints," depending on the database).

[25] PRESIDENT'S COUNCIL OF ADVISORS ON SCI. & TECH., EXEC. OFF. OF THE PRESIDENT, FORENSIC SCIENCE IN CRIMINAL COURTS: ENSURING SCIENTIFIC VALIDITY OF FEATURE-COMPARISON METHODS 96 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/PCAST/pcast_forensic_science_report_final.pdf [https://perma.cc/PGG6-2KS7].

[26] *Id.* at 96–98.

[27] *Id.* The PCAST Report suggests only reporting this upper bound of the chances of error to a jury, something which we disagree with, and which we will discuss later in this paper.

test a number of times, it is possible to estimate the false negative rate using the equation above: the number of false negatives divided by the sum of the false negatives and the true positives. Now, since we are discussing only one set of fingerprints in the case of the Madrid bombings, the denominator is at most one. This is because there is only one true match, and it could be either a false negative or a true positive, depending on the test outcome. Thus, whether we correctly identified the fingerprint or not, the fact that we have only one data point means the IAFIS results on the Madrid bombings cannot help us determine a reasonable false negative rate to apply to its matching algorithm.

Instead, we turn to a study that calculated the rate of false negatives in manual fingerprint identification.[28] A 2011 study compiled 520 matched pairs (composed of one latent and one non-latent fingerprint) and 224 non-matched pairs of fingerprints.[29] Each of the 169 examiners was given a mix of matched and unmatched fingerprints and were asked to identify whether they were a match, a non-match, or inconclusive.[30] The study found 450 false negatives out of 5,969 comparisons.[31] This indicates a false negative rate of about 1 in 13 (450 of 5,969, which is 7.5 percent).[32] Although there were differences in the number of false matches by examiner, most made errors. The study reported that "[e]ighty-five percent of examiners made at least one false negative error, despite the fact that sixty-five percent of participants said that they were unaware of ever having made an erroneous exclusion after training."[33] In other words, manual fingerprint matching is subject to substantial error, and nearly all experts make such errors. Based on the above discussion, we can summarize the error rates due to false positives and false negatives with the following table:[34]

	Computer	**Manual**
False Positive Rate	1 in 100,000	1 in 24
False Negative Rate	Unknown	1 in 13

Table 2: Approximate Error Rates in Fingerprint Identification

[28] Bradford T. Ulery et al., *Accuracy and Reliability of Forensic Latent Fingerprint Decisions*, 108 PROC. NAT'L ACAD. SCI. 7733 (2011).
[29] *Id.* at 7734.
[30] *Id.* at 7736.
[31] *Id.* at 7733.
[32] *Id.* at 7736.
[33] *Id.*
[34] Recall that 1 in 24 was the higher of the two rates found in black box studies.

IV. MADRID PART II—STATISTICAL CHANCES BEHIND THE MATCH

While fingerprint matching is imperfect, the Madrid fingerprint seemed like a slam-dunk. The identity was first narrowed down from millions of possible matches through IAFIS, then matched out of the top twenty selections by an expert, and finally verified by a second expert.

There is only one problem: they were all wrong. Brandon Mayfield, the lawyer who was arrested, had nothing to do with the Madrid bombings. The FBI, in fact, had found no other evidence linking him to the bombings, and he had not even traveled to Spain as he and his wife both had expired passports.[35] Why, then, was he even in the criminal FBI database? Mayfield was arrested for burglary as a teenager. Furthermore, all charges had been dropped.[36]

So, what went wrong? Recall that IAFIS acted as a screening tool, identifying twenty close matches out of 2 million fingerprints. Of those, an expert found one match. Then a second expert validated that match. From a statistical vantage point, even ignoring the other evidence of Mayfield's innocence, we will see that the fingerprint evidence was weak. To understand this conclusion, we use a 300-year-old theorem called Bayes' Rule, which quantifies probabilities when certain facts are known.[37] These probabilities are called conditional probabilities.[38] With Bayes' Rule, we can use the false negative and positive rates calculated above, along with other information, to evaluate a probability that is more meaningful.

Now we have found a matching fingerprint, what are the chances it belongs to the same person who touched the bag of explosives? Bayes' Rule determines the percentage of positive matches that are the true match. Before going into the math behind Bayes' Rule, consider an example of a test for the flu. Assume the false positive rate is 1 in 24 and the false negative rate is 1 in 13.[39]

Assume further that only 1 in 20 people who go to the doctor with flu symptoms actually have the flu. Now suppose 1,000 people go to the doctor with flu symptoms and all are given a flu test. About 950 of those with symptoms will not have the flu, but about 40 (1 in 24) will test positive for the flu. About fifty will have the flu and about forty-six of them (12 in 13) will test positive for the flu. Thus, of the 1,000 people, about 86 will test positive, and 46 out of 86 (54 percent) will actually have the flu. Now imagine yourself as one of those people who came in with flu symptoms and tested positive. Based on Bayes' Rule, there is a forty-four percent chance you actually have

[35] OIG Report, *supra* note 10, at 58.
[36] *Id.* at 31.
[37] *Bayes' Theorem*, STAN. ENCYCLOPEDIA PHIL. (Sept. 30, 2003), https://plato.stanford.edu/entries/bayes-theorem/ [https://perma.cc/LT42-PPF5].
[38] *Id.*
[39] Note that these are the same as the false positive and negative rates for fingerprints.

the flu. In other words, even though the test seems very good (getting it wrong either 1 in 24 or 1 in 13 times, depending on whether or not you have the flu), testing positive still is not a definitive result, and only tells you that you have about a 50/50 chance of having the flu.

A. *Mathematical Details*

We will see shortly that this is analogous to the fingerprint example, but we first go through the mathematical calculations. To simplify the discussion below, we introduce some statistical notation. When we write P(Event A), this means the probability of Event A (this is typically shortened to just "P(A)"). The vertical line ("|") means "given" and thus "P(A|B)" means the probability of Event A given that we know Event B occurred. We use the letter "U" to indicate that either of two events occurred (the "union"). We use an upside-down letter "U" to indicate that both of two events occurred (the "intersection"). Thus, when we write $P(A \cap B)$, we mean the chances of both A and B occurring.

Returning to the question of the matching fingerprint, we want to know P(Match|Positive Test Result). A positive test result means our test found a matching fingerprint, whereas a match means the fingerprint matches an individual (recall that when we use a test to compare a match, a True Positive or a False Negative can occur). We can use a Venn Diagram as a helpful tool to think about this probability (shown below).

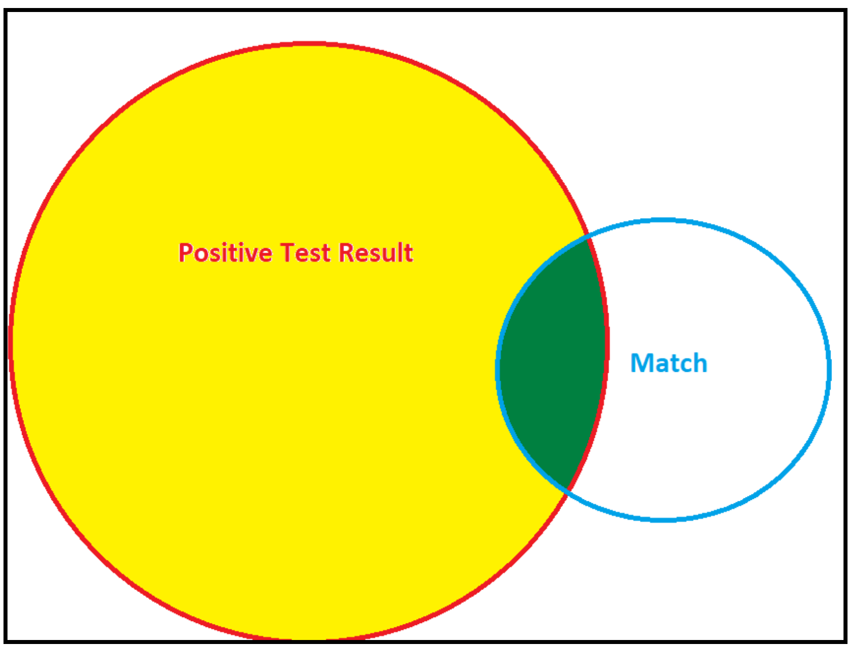

Figure 3: Venn Diagram of Match Chances

The red circle, "Positive Test Result," denotes the result we have obtained. We want to know the chances corresponding to the green shaded area (a matching fingerprint), conditioned on that Positive Test Result. To figure out these chances, we need to find out the size of the green area relative to the size of the red circle. In probability terms, this equates to the following:

$$P(\text{Match }|\text{Positive Result})=\frac{\text{P(Match}\cap\text{Positive Result)}}{\text{P(Positive Result)}}$$

Equation 1

The above equation can be used to relate the conditional probability of a match to the intersection of a positive result and a match. We can solve for the intersection as follows:

$$\text{P(Match}\cap\text{Positive Result)=P(Match}|\text{Positive Result)*P(Positive Result)}$$

And, using the same type of equation, we can generate:

$$\text{P(Match}\cap\text{Positive Result)=P(Positive Result}|\text{Match)*P(Match)}$$

Equation 2

In other words, we can determine the intersection in two different ways. If we can determine what Equation 2 equals, we have the numerator of Equation 1, and we are halfway to knowing the chances of a match, given a positive result.

The denominator of Equation 1, P(Positive Result), can be broken into two parts, the chance of a Positive Result and a Match and the chance of a positive result and No Match:

$$\text{P(Match}\cap\text{Positive Result) and P(No Match}\cap\text{Positive Result)}$$

These two added together equal the denominator. Using the same idea as in Equation 2, we can arrive at the following:

$$\text{P(No Match}\cap\text{Positive Result)= P(Positive Result}|\text{No Match)*P(No Match)}$$

Equation 3

Thus, the numerator is Equation 2, and the denominator is Equation 2 plus Equation 3. Recall that Table 1 above gives us the False Positive Rate and the False Negative Rate. Using probability terminology, the False Positive Rate is P(Positive Result|No Match) and the False Negative Rate is P(Negative Result|Match). Since we are focusing on the manual portion of the investigation, we will focus on the chances of a manual match. For manual checking, the False Negative Rate we identified is about 1 in 13. This means that about 12 in 13 times (about 92 percent) we get a positive result given there is a match. Thus, on the right side of Equation 2, P(Positive Result|Match)=12/13= ninety-two percent.

From Table 1, the False Positive Rate for manual checking is 1 in 24, which is about four percent. This is the first term in Equation 3. Now, if we have P(Match) and P(No Match), we can find the chances: P(Match|Positive Result).

Therefore, using the False Positive and Negative Rates, the chances of a Match, given the positive test result, are

$$\frac{.925*P(\text{Match})}{.925*P(\text{Match})+.042*P(\text{No Match})}$$

Equation 4

Now we have narrowed the problem to determining the probability of a match. We know IAFIS returned twenty names and only one could possibly match. Therefore, in the best-case scenario for finding the match, one of the twenty names returned is the match (i.e., the chance of a match is 1/20, or 0.05). Likewise, at least 19/20 (0.95) are not a match. Thus, for the highest chances of a match, we use the numbers we used in the flu example above. Using Equation 4 and these probabilities, the numerator is .925*(.05) = .925 = .046. The denominator is: Numerator + .042*.95 = .046 + .040 = .086. Dividing the numerator by the denominator, we obtain .046/.086, which is approximately a fifty-four percent chance.[40]

Thus, even without looking at other evidence, and assuming that the match is among the twenty fingerprints identified by IAFIS, there is only a fifty-four percent chance the identified fingerprint will be the match.[41] Furthermore, the chances are only this high if the match is in the database and identified by IAFIS as one of the twenty. Given the bombings were in Spain, and the SPN believed the perpetrator was Moroccan, it was far from a guarantee that IAFIS would have contained the suspect's fingerprints. Suppose there was only a 50/50 chance of IAFIS containing the matching fingerprint. In such a case, the numerator becomes .925*.05*.5 = .023. The denominator becomes .023 + .042*(1-.05*.5) = .064. The chance of a match given a positive result thus would be thirty-six percent (.023/.064).

[40] Bayes' Rule inherently assumes there may be multiple matches, and we are considering one of those matches. Assuming an expert stops at the first positive result, the chances that this particular result will be a match are sixty-five percent. Though a little higher, this is still well short of "proof" that the positive result is a match.

[41] This ignores the fact that the manual checker would likely not identify two matches, since the expert knows the fingerprint only belongs to one person. However, one could think of the result as considering situations where each expert looks at a single fingerprint. About half the ones identified as matches will be right and about half will be wrong.

In the Madrid bombing case, one might think the fact that the review was verified would reduce the chances of a false positive. However, the second review was not performed independently.[42] The second reviewer was not given all potentially matching fingerprints—only the Mayfield fingerprint.[43] The second reviewer was aware not only of the other reviewer's identification but also of the interpretations of some of the potential differences.[44] These facts alone indicate that the verification might have a very high chance of being just another false positive. Furthermore, two other reviewers, who did not officially perform a second review, doubted that the fingerprint was a match.[45]

In retrospect, despite the relatively low false positive rate of fingerprint matching, the identified fingerprint had at best a little better than a 50/50 shot of being a correct match. Given the evidence and knowledge of the SNP, the 50/50 chances should have been discounted further still.

V. CURRENT POLICY AND IMPLICATIONS

The use of fingerprint evidence in court goes back 100 years in the United States.[46] In the 1910 case of *People v. Jennings*, a fingerprint found at the scene of a crime was used to help convict an assailant and even survived an appeal.[47] Fingerprint evidence is often introduced to the court through an expert, who might opine, for example, that fingerprints found on a weapon "match" those of the defendant. According to the U.S. Department of Justice, "latent fingerprint identifications are subject to a standard of 100 percent certainty."[48]

As evidenced in the Madrid case, the 100 percent standard does not comport with reality. Despite this fact, and the *Daubert* standard regarding the admissibility of scientific expert evidence[49] (as discussed below), fingerprint matches are still widely accepted, apparently "grandfathered" in due to their use for over a century.[50] For our part as statisticians, we do not believe that

[42] OIG Report, *supra* note 10, at 32.
[43] *Id.* at 32–33.
[44] *Id.*
[45] *Id.* at 33.
[46] Francine Uenuma, *The First Criminal Trial that Used Fingerprints as Evidence*, SMITHSONIAN MAG. (Dec. 5, 2018), https://www.smithsonianmag.com/history/first-case-where-fingerprints-were-used-evidence-180970883/ [https://perma.cc/2SF2-AN4P].
[47] *See generally* People v. Jennings, 96 N.E. 1077 (Ill. 1911).
[48] OIG Report, *supra* note 10, at 8. A latent fingerprint is one that is found at the scene of a crime or is otherwise left accidentally. Ulery, *supra* note 28, at 7733. This is in contrast to fingerprints that are used to identify people for security purposes, where the match is made using carefully made prints. *Id.*
[49] *See infra* note 50 and accompanying text.
[50] Brandon L. Garrett, *The Reliable Application of Fingerprint Evidence*, 66 UCLA L. REV. DISCOURSE 64, 67–68 (2018).

fingerprint and other identification evidence should be barred from courts. Barring fingerprint evidence would be an acknowledgement that it is flawed.

However, we also do not believe 100 percent certainty should be required. Such treatment would ignore the fact that all identification evidence, including eyewitness testimony, is known to be far from 100 percent reliable. If all evidence was barred where there was uncertainty, there would be nothing left for the jury to consider. A recent review of more than 2,000 exonerations indicated that about one in four included "false or misleading forensic evidence."[51]

Though not requiring 100 percent certainty, general legal standards do require some level of scientific precision. Federal Rule of Evidence 702, which includes the *Daubert* standard, requires that an expert opinion rely on relevant "sufficient facts and data" and "reliable principles and methods" "reliably applied."[52] Fingerprint evidence has long been considered reliable, but, as described above, has only recently come under scientific scrutiny. A recent article points out that courts have barely considered the reliability of the methods themselves or that a particular "expert" may not be comporting to general standards.[53] One possibility is that the courts could require testing and licensure. The IAFIS database could then be used to identify similar fingerprints and test examiners. Only those examiners passing a test with sufficiently low false positive and negative rates would be licensed to testify in court. Presumably, though, even such licensed experts would still occasionally mis-identify fingerprints.

Even with licensure that limits experts to a low false positive rate, in situations where millions of fingerprints are run, there is a high chance of a false match, simply due to the high number of fingerprints being checked. Indeed, the problem in the Madrid case was not the false positive rate per se. Instead, the problem occurred because so many fingerprints were considered. With a false positive rate of 1 in 24, a false positive becomes more likely than not when just seventeen fingerprints are examined.[54] Using an electronic database to first cull fingerprints to a few dozen close matches, a manual examiner will almost always find a match, regardless of whether the true match is among the fingerprints, simply due to the math of the false positive rate.

For a jury to fairly consider fingerprint evidence, the number of

---

[51] Mejia et al., *supra* note 9, at 25.
[52] FED. R. EVID. 702; Daubert v. Merrell Dow Pharm., Inc., 509 U.S. 579, 589 (1993).
[53] Garrett, *supra* note 50, at 77–79 ("Judges should carefully examine not just whether a method is generally reliable, but the reliability of a particular expert and the work done in a particular case.").
[54] The chances of not finding a false match are 23/24. When seventeen fingerprints are considered, these chances are (23/24) to the power of seventeen, which is forty-nine percent, meaning there is a fifty-one percent chance of finding a false match when seventeen fingerprints are considered. The chances continue to increase as more fingerprints are considered.

fingerprints examined must be revealed, as well as the potential range of the false positive rate and false negative rate, and what that means in terms of the chances of a false match. In such a situation, a fingerprint match can be treated like any other piece of circumstantial evidence. For example, the fact that witnesses saw a red pickup truck at the crime scene and the suspect drives a red pickup truck could be relevant, but, if one in twenty people drive a red pickup truck, then this would not be particularly important without other evidence. Fingerprint evidence is similar.

The main issue with identification evidence, especially in an age where we can examine large databases, is its history of being seen as 100 percent proof. It is far from that. Like most scientific tests, there is a chance a fingerprint test may be incorrect. We see nothing wrong with juries considering such tests, as long as they are aware of those chances and the context of the test. We next turn from the use of data science in identification evidence to its use in guiding and evaluating policy decisions.

VI. OPIOID CRISIS—SHOULD WE HAVE SEEN IT?

The seeds of the opioid epidemic can be traced to a false scientific notion that opioids were not addictive. According to an overview article on opioids, "this widespread belief was based upon two small retrospective publications from the 1980s[.]"[55] This belief, along with growing concerns regarding chronic pain, led to the increased use of opioids, which had formerly been used mostly for pain in cancer patients.[56] A number of other factors fueled the fire, not the least of which was the push for greater use of opioids by pharmaceutical companies.[57] Though unseen by the public for years, the U. S. Drug Enforcement Administration (DEA) tracked the spread of opioids.[58] The Washington Post and HD Media Co., L.L.C. sued to gain access to the DEA data, held in its so-called Automation of Reports and Consolidated Orders System (ARCOS) database.[59] The ARCOS data gives granular detail of prescriptions by pharmacy, manufacturer, and geography.[60]

---

55 Mark R. Jones et al., *A Brief History of the Opioid Epidemic and Strategies for Pain Medicine*, 7 PAIN & THERAPY 13, 15 (2018).
56 *Id.*
57 *Id.* at 16.
58 *See Five Takeaways from the DEA's Pain Pill Database*, WASH. POST (July 16, 2019, 7:24 PM), https://www.washingtonpost.com/investigations/six-takeaways-from-the-deas-pain-pill-database/2019/07/16/1d82643c-a7e6-11e9-a3a6-ab670962db05_story.html [https://perma.cc/43ZP-HT9C].
59 *See Drilling into the DEA's Pain Pill Database*, WASH. POST (Jan. 17, 2020), https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/ [https://perma.cc/NL6Y-2ZCJ].
60 *Automation of Reports and Consolidated Orders System (ARCOS)*, U.S. DEP'T JUST., https://www.deadiversion.usdoj.gov/arcos/index.html [https://perma.cc/CJR9-NURX].

A number of news reports, special studies, and countless lawsuits have chronicled the impact of opioids. The major focus of the previous work on opioids has centered around the number of opioid-related deaths and the numerous hypotheses with respect to the cause(s). The following list represents a subset of the reasons experts have provided to explain the cause of the opioid epidemic:

1. Changes in the physicians' attitudes about prescribing pain killers;

2. Increased access through family members and friends;

3. Aggressive marketing of the painkillers;

4. Inadequate policies and procedures for monitoring the distribution of painkillers;

5. Declining economic conditions; and

6. Understating the addictive nature of the drugs. [61][62]

While we believe using the number of deaths resulting from opioid use is an appropriate method for quantifying the impacts of the opioid epidemic, one area that has not garnered much attention is the strain opioids have placed on state budgets. These fiscal impacts have lasting effects because they require states to increase labor in certain fields during the crises, forcing state governments to establish programs for abating the cost of the opioid epidemic in the future. Given this perceived omission of tracking the opioid epidemic, we have elected to focus on how governors have been forced to address the opioid epidemic by the use of state funds. More specifically, this analysis will focus on comparing states with and without prescription drug monitoring programs (PDMP) to quantify the increase in state-paid employees in the areas of law enforcement, medical services, and social services.

A. *Data Used*

The data used in the opioid analysis was derived from multiple prepackaged datasets. Specifically, we used opioid death and distribution data, state-level regulatory policies, population, and employment data. Although each dataset covered different starting and ending years, the major focus of our

---

[61] Abbey E. Alpert et al., *Origins of the Opioid Crisis and Its Enduring Impacts* 1–2, 6, 18 (Nat'l Bureau of Econ. Research, Working Paper No. 26500, 2019).

[62] Melissa Healy, *Who's to Blame for the Nation's Opioid Crisis? Massive Trial May Answer that Question*, L.A. TIMES (Sept. 18, 2019, 5:00 AM), https://www.latimes.com/science/story/2019-09-17/opioid-lawsuit-who-is-to-blame [https://perma.cc/KV2G-EJZB].

dataset was dictated by the 2006 to 2017 data provided in the ARCOS Report 2 dataset.[63]

B. *Opioid Death and Distribution Data*

The drug data used reflects opioid overdose deaths by state per 100,000 people gathered from the Centers for Disease Control and Prevention (CDC) drug overdose mortality database.[64] The data within this dataset ranges between 1999 and 2016 and is reported at the state level.[65] We used the distribution data in the ARCOS Report 2, which includes state quarterly data for seven Schedule II drugs, in which we only used Oxycodone. We used annual total grams based on the summation of the quarterly distribution counts.

C. *Population Data*

The population data used in this analysis was based on state-level population projections produced by the U.S. Census Bureau from the 2000 and 2010 Censuses. These datasets included all residents of each state—not just the states' residents older than 16 years of age[66]—and were combined with the ARCOS data to calculate the number of grams supplied to each state per resident. According to this calculation, Delaware (2) and Florida (3) comprise the top-five grams of Oxycodone supplied per resident in the dataset. In contrast, Illinois (3) and Texas (2) comprised the bottom-five in terms of the grams per resident calculation.

D. *Employment Data*

The employment data was gathered from the Bureau of Labor Statistics (BLS) at the industry and state level and classified by NAICs codes, which allowed us to identify "impacted labor" in Social Assistance (e.g., Child and Youth Services, Community Housing Services, etc.), Medical Professions

[63] Washington, D.C. is not included in the analyses because each dataset used does not include observations from Washington, D.C.
[64] *Drug Overdose Mortality by State*, CENT. FOR DISEASE CONTROL & PREVENTION (Feb. 13, 2020), https://www.cdc.gov/nchs/pressroom/sosmap/drug_poisoning_mortality/drug_poisoning.htm [https://perma.cc/W2CR-DYC7].
[65] *Id.*
[66] U.S. CENSUS BUREAU, METHODOLOGY FOR THE INTERCENSAL POPULATION AND HOUSING UNIT ESTIMATES: 2000 TO 2010 1 (2012), https://www2.census.gov/programs-surveys/popest/technical-documentation/methodology/intercensal/2000-2010-intercensal-estimates-methodology.pdf [https://perma.cc/ZA5B-X2KP]; *State Intercensal Tables: 2000-2010*, U.S. CENSUS BUREAU (Nov. 30, 2016), https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-state.html [https://perma.cc/N93C-KULU]; *State Population Totals and Components of Change: 2010-2019*, U.S. CENSUS BUREAU, https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html [https://perma.cc/6TP4-3PRT].

(e.g., Mental Health Practitioners, Ambulatory Health Care Services, etc.), and Law Enforcement (e.g., Correctional Institutions, Courts, etc.).[67]

E. *State Regulatory Policies*

The state legislation of the PDMP is provided by a 2018 training and technical assistance document produced by the Heller School at Brandeis University.[68] The document provides the year in which each state initiated their respective PDMP.[69] We were agnostic while performing the analyses regarding the state agency that housed the PDMP, the method, or timing of reporting prescriptions because there has not been a standardization of these practices.

The table below provides the year in which states started their respective PDMP after 2005.[70] We selected 2006 as our cutoff date because it represented the first year of the ARCOS data. Of those states starting programs before 2006, California initiated the first PDMP, starting the state's program in 1939; Hawaii followed closely in 1943.[71] Colorado, Mississippi, North Carolina, North Dakota, and Illinois were the last states to implement programs prior to the 2006 cutoff.[72] According to the Brandeis report, Missouri was the only state that did not have an established state-wide program as of March 2018.[73]

---

[67] *Databases, Tables & Calculators by Subject*, U.S. BUREAU OF LAB. STAT., https://www.bls.gov/data/#employment [https://perma.cc/M8D4-HSCZ].
[68] *See* BRANDEIS UNIV., HISTORY OF PRESCRIPTION DRUG MONITORING PROGRAMS (2018), https://www.pdmpassist.org/pdf/PDMP_admin/TAG_History_PDMPs_final_20180314.pdf [https://perma.cc/UD7B-MUGC].
[69] *Id.*
[70] *Id.*
[71] *Id.*
[72] *Id.*
[73] St. Louis County, MO does have a PDMP program in place as of 2018. *Id.*

Year	State(s) Initiated
2006	Connecticut, Iowa, Louisiana, South Carolina, Vermont
2007	Arizona, Minnesota, Washington
2008	Alaska, Kansas, New Jersey
2009	Florida, Oregon
2010	Delaware, South Dakota, Wisconsin
2011	Arkansas, Georgia, Maryland, Montana, Nebraska
2012	New Hampshire

Table 3: Prescription Drug Monitoring Program[74]

We combined the five datasets by matching through year and state, resulting in one dataset containing population, employment, opioids supplied, opioid death rate, and PDMP status for each state in our analysis.

F. *Analytic Approach*

Since we sought to understand the impact of PDMPs on state budgets and the opioid crisis, we began by establishing two comparison groups: established states and transitioned states. A state was defined as an Established State if it implemented a PDMP before 2006. In contrast, a state was defined as a Transitioned State if it implemented a PDMP between 2006 and 2017. The aforementioned bifurcation of pre and post-2006 regarding PDMP establishment allowed us to compare Established States versus Transitioned States, but also Transitioned States pre- and post- PDMP implementation. Therefore, we constructed two comparison groups: (1) Established versus Transitioned and (2) Pre-Transitioned versus Post-Transitioned.

i. Comparison Group 1: Established Versus Transitioned States

The following two graphs reflect the number of opioid deaths per 100,000 residents and the grams of Oxycodone supplied per resident. As the figure below shows, the average number of opioid related deaths was higher for states with established PDMPs between the years of 2006 and 2017. Specifically, the average for the Established States had a 9.98 average while the Transitioned States had a 7.93 average.

[74] BRANDEIS UNIV., *supra* note 68.

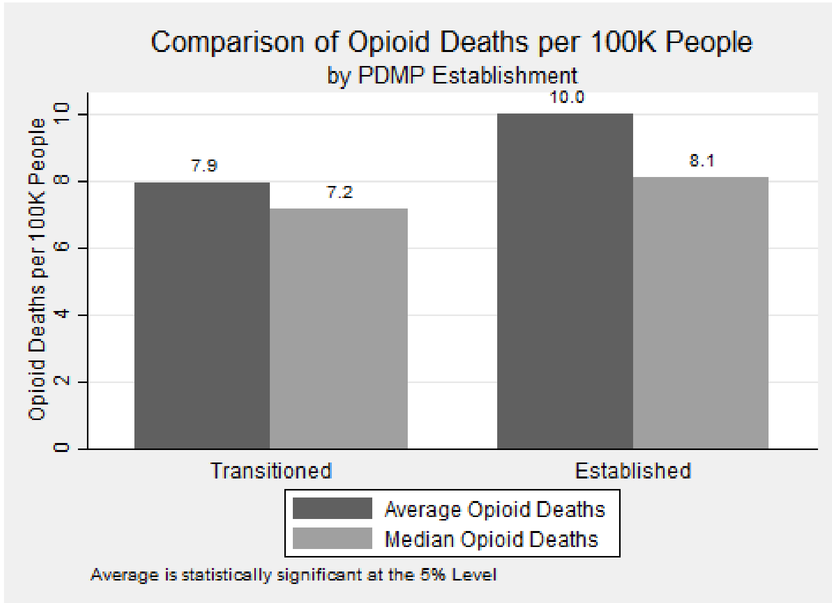

Figure 4: Opioid Deaths by PDMP Status

In contrast, the grams supplied per resident is lower for the Established category than the figure for the Transitioned category. Specifically, the Established States figure is approximately .18 grams per person as compared to .20 for the Transitioned States.

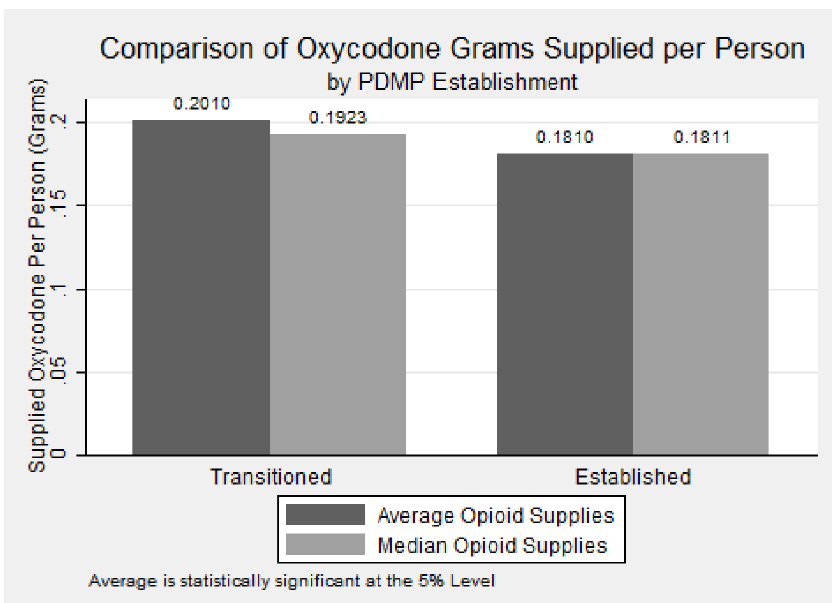

Figure 5: Oxycodone Prescriptions by PDMP Status

The table below is designed to report the additional labor cost for states that initiated PDMPs prior to 2006. In addition to accounting for the existence of an established PDMP, we also accounted for the population of each state under the assumption that higher populations intuitively require higher levels of state employment. As shown, even after accounting for the number of residents in each state, the states that had established PDMPs had higher annual average salaries for state-employed professions in the medical, social, and law fields. Specifically, medical labor costs were approximately 15.7 percent higher in the states with established PDMPs. According to this data, the social labor field did not have a statistical difference between Established and Non-Established states.

Variable	Medical Labor	Social Labor	Law Labor
Natural Log of Population	0.0680***	0.07397***	0.0167*
Established Flag	0.1576***	0.0162	.03307*
_cons	9.6948***	9.8420***	10.7883***
N	324	347	594

*Note: * p<.1; ** p<.05; *** p<.01*

Table 4: Labor Cost Differences by Established PDMPs

ii. Comparison Group 2: Pre-Transitioned Versus Post-Transitioned

The Transitioned States allowed for a natural experiment to take place. For a natural experience to occur, an exogenous event (such as implementing a PDMP) must take place. This event creates two groups: the control group and the treatment group. The exogenous event does not affect the control group. However, the event affects the treatment group. In this case, our control group is the Transitioned State *before* implementation and our treatment group is the Transitioned State *after* implementation.

Reporting the same statistics provided above, we illustrate graphs of states that experienced (1) a steady increase in grams per resident and volatility in the number of deaths (Arkansas), (2) a significant reduction in supplies and a substantial increase in deaths (Florida), (3) a minor reduction in supplies and a significant increase in deaths (Maryland), and (4) a reduction in the supply of opioids and a steady reduction in opioid related deaths (Oregon). Interestingly, opioid related deaths increased post program implementation and reported supplies per person increased post implementation.

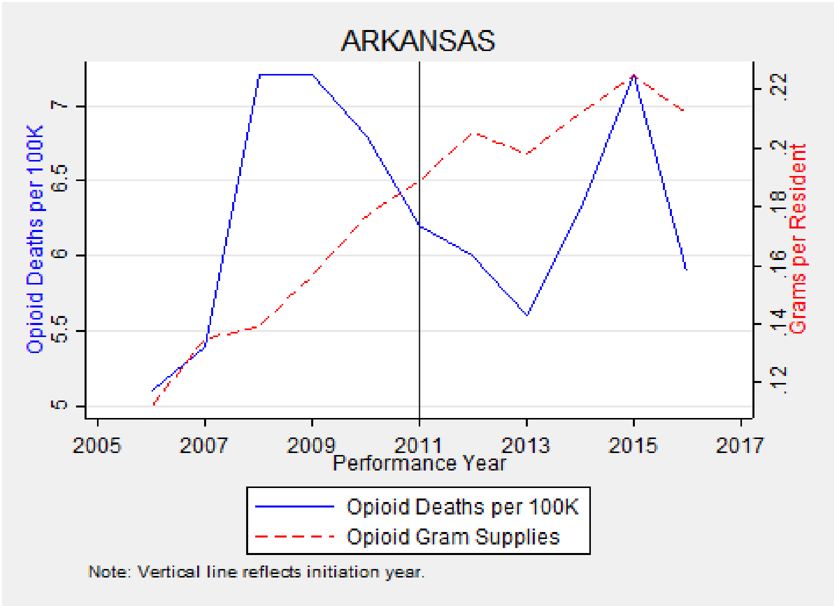

Figure 6: Arkansas Opioid Deaths and Supplies

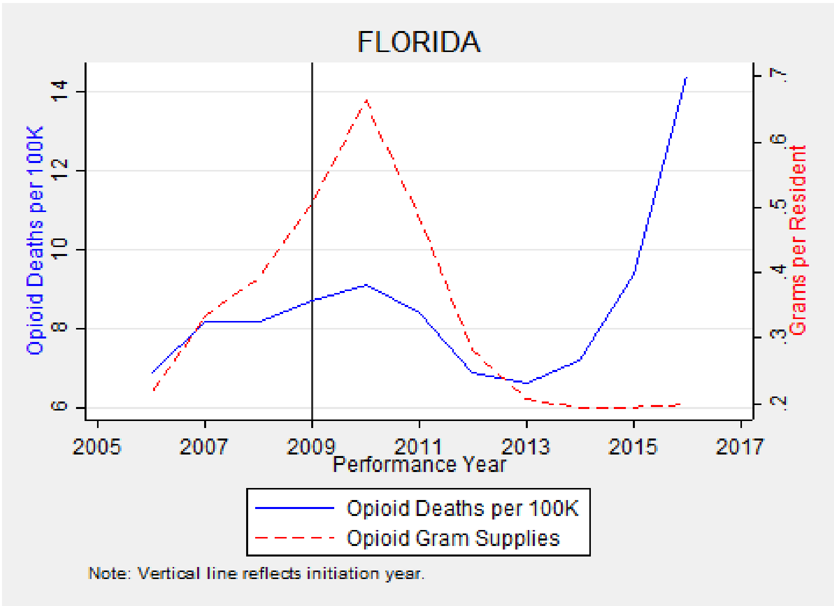

Figure 7: Florida Opioid Deaths and Supplies

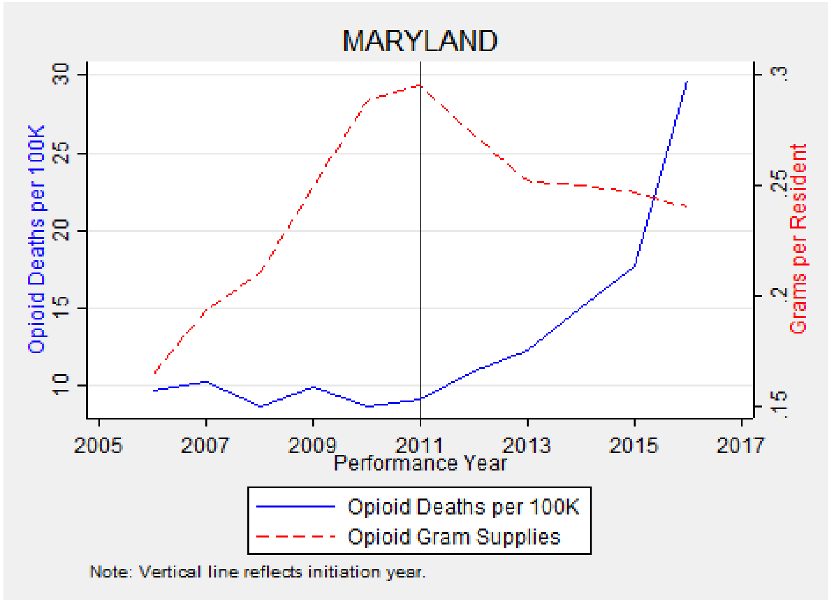

Figure 8: Maryland Opioid Deaths and Supplies

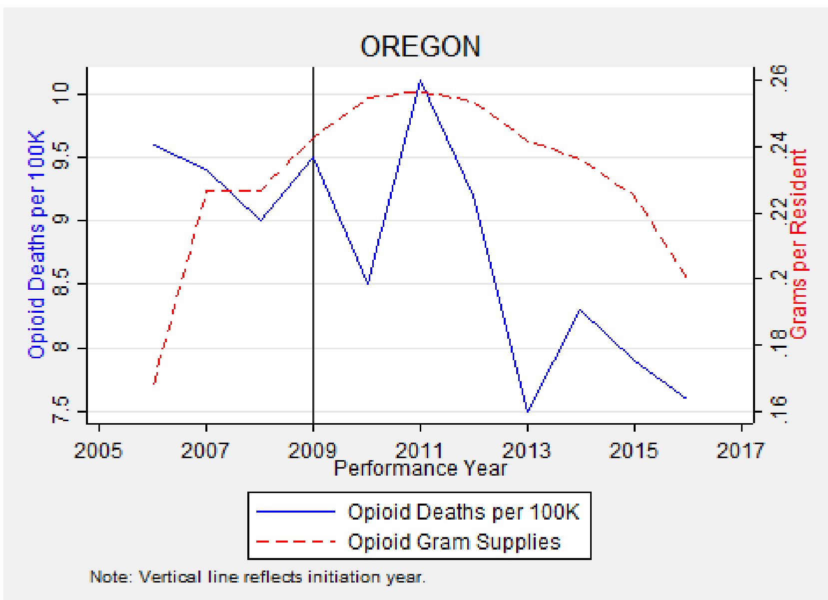

Figure 9: Oregon Opioid Deaths and Supplies

To better understand the changes within a state, we created a one-year PDMP implementation lag to capture any delayed response to, or enforcement of, the PDMP. For example, according to Table 3, Delaware initiated their

PDMP in 2010, so the one-year lag is 2011. We also created a two-year lag to account for additional preparation and enforcement time for the state. In this example, Delaware's two-year lag is 2012. The rationale for the lags is shrouded with the understanding that a new program typically requires a few months to accurately implement the necessary reporting tools and effectively enforce the program. Even if enforcement happens immediately, it is plausible that a state will continue receiving an increase in opioids until the reporting has been flagged as a concern. Additionally, since our PDMP data is annual, we are unaware of the implementation month. The findings for the respective lags for the Transitioned States are provided below. As the table below indicates, a consistent pattern does not exist.

State	Initiation Year	Deaths (percentage)			Supplies (percentage)		
		No Lag	One-Year Lag	Two-Year Lag	No Lag	One-Year Lag	Two-Year Lag
Wisconsin	2010	13.70	17.81	45.21	7.40	12.27	5.37
Delaware	2010	5.00	-23.33	6.67	9.73	-13.88	-27.72
South Dakota	2010	0.00	-31.11	-2.22	2.39	-2.32	-3.76
Maryland	2011	19.78	35.16	64.84	-6.83	-13.40	-13.59
Nebraska	2011	7.14	-21.43	14.29	3.82	2.31	6.30
Georgia	2011	0.00	-1.85	29.63	-6.63	-14.41	-12.54
Arkansas	2011	-3.23	-9.68	1.61	9.11	5.38	13.12
Montana	2011	-22.06	5.88	-20.59	5.85	4.98	5.37
New Hampshire	2012	12.38	122.86	198.10	-2.35	0.55	-6.40
Average		3.64	10.48	37.50	2.50	-2.06	-3.76

Table 5: Percentage Changes in Opioid Deaths and Supplies Post PDMP Initiation

Table 6 provides the additional labor costs incurred by Transitioned States after initiation of their PDMP program. To more effectively isolate the additional costs, we confined the analysis in the table to the states that implemented a PDMP after 2005. As shown in the table, the highest increase was in the medical costs with an increase of approximately 36.1 percent upon initiation of the program. In essence, if the annual salary was $75,000 before the implementation, the post-implementation salary was $102,000. Unlike the previous labor cost analysis, each of the three professional areas experienced statistically significant increases in the cost of labor partially attributed to the existence of a PDMP.

Variable	Medical Labor	Social Labor	Law Labor
Natural Log of Population	-0.0548	0.0400**	-0.0206
PDMP Program	0.3608***	0.2866***	0.2702***
_cons	11.4083***	10.1637***	11.1680***
N	100	161	275

*Note: * p<.1; ** p<.05; *** p<.01*

Table 6: Increases in Labor Cost Post Initiation of a PDMP

The work performed for the opioid analysis is ideal for building a repository of structured and unstructured data to better understand the epidemic. For example, the quantity of contracts, and communication could prove vital to performing in-depth opioid analyses. In conjunction with building the database through reliable data science practices, machine learning can be used to detect, analyze, and test relationships through numerous iterations. In essence, the combination of data science practices and machine learning allows for numerous opportunities for a better understanding of the opioid crisis.

VII. CIVIL POLICY IMPLICATIONS

Analysis similar to the work performed above avails itself for use by policy makers. Per our understanding of the matter, civil policy in response to the opioid crisis resides in the following two buckets: (1) litigation and (2) social awareness.

Bucket 1: Litigation

a. Identifying and proving that the suppliers and manufacturers contributed to the opioid crisis; and

b. Identifying and proving that medical professionals oversupplied their patients and illegally exchanged opioid prescriptions for money and other services.

Bucket 2: Social Awareness

a. Understanding the differences and subsequent effectiveness of the state programs designed to curb the opioid epidemic; and

b. Identifying areas of emphasis that will allow states and counties the most effective measures for responding to the current and future effects of the opioid crisis.

In terms of litigation implications, numerous lawsuits brought on the behalf of state and county plaintiffs have alleged that distributors understated the addictive nature of opioids and failed to monitor for suspicious orders as required by the U.S. Drug Enforcement Agency.[75] These lawsuits have focused mainly on Purdue Pharma, Johnson & Johnson, Cardinal Health, McKesson, and AmerisourceBergen.[76] The interesting thing about these cases is that they have striking similarities to previous nationwide matters—notably the tobacco settlements of the late 1990s and the residential mortgage crisis of the past fifteen years.[77] However, the major difference between the previous two crises and the opioid crisis are the plaintiffs (tobacco suits rarely included different individuals),[78] and the defendants (the mortgage defendants did not include individuals).[79] On the other hand, the significance of these two matters is that their learnings provide a framework for damage calculations,[80] and the expectation of the American public to see individuals prosecuted and not just their employers.[81] As an additional benefit, the tobacco settlement provides a framework for disaggregating the payments to the respective plaintiffs.[82] Another area of litigation receiving notice is the illegal exchange of opioid prescriptions by pharmacists, doctors, and other healthcare providers for services in return. For example, five states including Alabama, Kentucky, Ohio, Tennessee, and West Virginia have initiated cases against individuals who have carried out these lucrative opioid prescription plans.[83] The other area

---

[75] *Over 600 Lawsuits Against Opioid Companies Become One Federal Court Case*, WORKING PARTNERS (2018), https://www.workingpartners.com/over-600-lawsuits-against-opioid- companies-become-one-federal-court-case/ [https://perma.cc/3DRA-B7GJ].

[76] *See* Colin Dwyer, *Your Guide to the Massive (and Massively Complex) Opioid Litigation*, NAT'L PUB. RADIO (Oct. 15, 2019, 9:05 AM), https://www.npr.org/sections/health-shots/2019/10/15/761537367/your-guide-to-the-massive-and-massively-complex-opioid-litigation [https://perma.cc/YDL3-BPEY].

[77] *See generally* Maribeth Coller et al., *Evaluating the Tobacco Settlement Damage Awards: Too Much or Not Enough?*, 92 AM. J. PUB. HEALTH 984 (2002) (discussing tobacco settlement damages during the last half of the twentieth century); Faten Sabry et al., *Credit Crisis Litigation Revisited: Litigating the Alphabet of Structured Products* 2, NERA ECON. CONSULTING (June 4, 2010) (discussing litigation follow the mortgage crisis during the early twenty-first century), https://www.nera.com/content/dam/nera/publications/archive2/PUB_Credit_Crisis_Litigation_Revisited_0610(1).pdf [https://perma.cc/2UH8-KN7L].

[78] Kathleen Michon, *Tobacco Litigation: History & Recent Developments*, NOLO, https://www.nolo.com/legal-encyclopedia/tobacco-litigation-history-and-development-32202.html [https://perma.cc/LL7LF-JEN3].

[79] *See* Sabry et al., *supra* note 77.

[80] *See generally* Coller et al., *supra* note 77.

[81] Joe Pinsker, *Why Aren't Any Bankers in Prison for Causing the Financial Crisis*, ATLANTIC (Aug. 17, 2016), https://www.theatlantic.com/business/archive/2016/08/why-arent-any-bankers-in-prison-for-causing-the-financial-crisis/496232/ [https://perma.cc/F3ZY-PB9J].

[82] *See generally Master Settlement Agreement*, PUB. HEALTH L. CTR., https://publichealthlawcenter.org/topics/commercial-tobacco-control/commercial-tobacco-control-litigation/master-settlement-agreement [https://perma.cc/9J42-GN28].

[83] Campbell Robertson, *Doctors Accused of Trading Opioid Prescriptions for Sex and Cash*, N.Y.

that has received attention from the U.S. Department of Justice in recent months is the identification of physicians that statistically oversupply their patient communities when compared to other physicians in the same field and with similarly sized patient communities.[84] Given the magnitude of the opioid epidemic, we anticipate these and other cases will continue into the future as we realize substantial impacts of the opioid epidemic in the coming years.

The civil policy implications in the social awareness bucket will play a major role in ensuring the nation's ability to reduce the impact of the opioid epidemic. This response can be rooted in, but not limited to, the following two areas:

1. Understanding the difference in effectiveness of the PDMPs mentioned in this article; and

2. Increasing the needed resources (i.e., money and skilled professionals) to withstand the current and residual impacts of the lingering opioid epidemic.

When considering the effectiveness of the PDMPs, the ability to differentiate the causes of program performance between seemingly high and low performing states is crucial. For example, what has allowed California to have an average opioid related death rate of approximately 4.79 between 2006 and 2016, whereas much chronicled West Virginia had an average of approximately 26.31 over the same time period? Is it simply due to the age of California's program that was initiated in 1939 in comparison to West Virginia's that was initiated in 1995, or are there other factors that explain the differences? Do states that statistically outperform their counterparts in death and supply statistics revisit the effectiveness of their programs on a more consistent basis creating additional opportunities for improvement, and/or do they levy fines and damages to any noncompliance of the respective program's requirements? As previously stated, the ability to answer that and other questions that will arise could allow states, such as Florida and Maryland, to understand how states, like Arkansas and Oregon, have been able to realize reductions in the number of opioid related deaths since their respective programs' initiations.

The other area that currently requires and will continue to require increased attention of policy makers is securing the appropriate resources to combat the pressures placed on communities due to the opioid epidemic. These resources include the funding necessary to build the facilities needed for

TIMES, Apr. 18, 2019, at A18.

[84] *See* Karma Allen, *California Doctor Charged with Murder in Several Opioid-related Deaths*, ABC NEWS (Aug. 15, 2019, 8:48 PM), https://abcnews.go.com/US/california-doctor-charged-murder-opioid-related-deaths/story?id=65004516 [https://perma.cc/3GGH-UZDV].

short-term and long-term care for the more than two million Americans that are considered opioid abusers, not including fentanyl and other illicit forms of opioids.[85] Building the facilities for the abusers is only a fraction of the response, staffing the facilities with trained professionals equipped with the necessary skills to help rehabilitate their patients will also require a concerted effort by local policy makers. A community's ability to successfully reintroduce their patients to society will be paramount to the viability of each community. Intuitively, the communities that can return their patients to relatively more normal standards of living will experience dramatic improvements in social welfare when compared to their counterparts that are not as successful. An additional area of concern for policy makers is the structural impacts on families due to the opioid crisis. Notably, the majority of the children of opioid abusers will require special forms of education for a period of time or for all of their schooling due to the lasting effects of their parents' drug use. According to the National Academy for State Health Policy, 1 in 3 out-of-home-placements in fiscal year 2016 was due to parental substance abuse.[86] As expected, this requires social workers and other community helpers to be able to identify and prove parental drug users are having negative effects on their children and to find suitable housing for these children once they have been removed from their parents' custody. As one can imagine, a community's ability to meet both stipulations requires a significant amount of coordination between community leaders and a great deal of luck.

VIII. CONCLUSION

The preliminary analyses presented demonstrate how analytics are able to quantify expected outcomes based on actual outcomes. Although the data used was retrieved from actual databases, they still provide results with a level of uncertainty. Our experience working with data serves as a constant reminder that the ability to analyze data is a necessary but insufficient condition for success. Successful data analytic projects are a healthy marriage between the statistician and the industry expert.

---

[85] *Statistics on Addiction in America*, ADDICTION CTR. (Dec. 5, 2019), https://www.addictioncenter.com/addiction/addiction-statistics/ [https://perma.cc/8S5A-9HLM].

[86] BECKY NORMILE ET AL., NAT'L ACAD. FOR ST. HEALTH POL'Y, STATE STRATEGIES TO MEET THE NEEDS OF YOUNG CHILDREN AND FAMILIES AFFECTED BY THE OPIOID CRISIS 3 (2018), http://www.inckmarks.org/docs/keyissues/OPIODSArticleNASHP.pdf [https://perma.cc/9XUM-Q3G5].