

System Reliability Analysis: Impact of Structural Anomalies in State Voter Registration Systems

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Abstract: This analysis examines fundamental reliability issues in state voter registration systems stemming from structural database anomalies and record reconciliation failures. Research reveals systemic inconsistencies that impair basic database functionality, including: irreconcilable discrepancies between state and county voting records, widespread record duplication (cloning), retroactive historical modifications, and algorithmically obscured data relationships. These issues create mathematical uncertainties in both individual and aggregate voter participation records that cannot be resolved through standard auditing procedures. The cumulative effect renders these systems incapable of reliably performing their core function of accurately tracking voter participation, independent of the original causes of these anomalies.

Keywords: Election integrity, Database reliability, Voter registration systems, Algorithmic manipulation, System security

1. Introduction

Voter registration databases serve as the authoritative record of electoral participation in the United States. Their primary function is to maintain accurate records of eligible voters and their participation in specific elections. This function requires consistent, traceable relationships between voters, their identification numbers, and their voting histories. Recent analysis of state voter registration systems has revealed structural anomalies that fundamentally compromise this basic functionality.

The reliability issues stem from four primary sources: irreconcilable disparities between state and county records, extensive duplication (cloning) of voter identification information, retroactive modifications to historical voting records, and the use of sophisticated voter ID assignment algorithms capable of covert tracking and manipulation of records. In one state's system alone, over 250,000 voting records differ between state and county databases for the same election and ID numbers, while maintaining nearly identical total vote counts through apparent vote reassignment between IDs (Paquette, 2023). Additionally, approximately 1.5 million cloned identification numbers have been documented in NY, with algorithmic evidence of 500,000 more deleted duplicates whose original voter associations remain recoverable.

These structural issues create cascading effects throughout the system that transcend questions of cause or intent. When state and county databases disagree on hundreds of thousands of voting records while reporting similar totals, or when millions of cloned IDs exist in the system, basic mathematical certainty becomes impossible. The system can no longer provide reliable answers to fundamental questions like "Who voted in this election?" or "How many unique voters participated?"

This analysis examines the technical implications of these anomalies and their impact on system reliability, focusing solely on functional outcomes rather than causes. The goal is to understand how these structural issues affect the system's ability to perform its core functions, regardless of how they originated.

1.1 Database Integrity Theory and Fitness for Use

Database consistency theory establishes that reliable systems must maintain fundamental ACID properties (Atomicity, Consistency, Isolation, Durability) to perform their core functions (Haerder and Reuter, 1983). These properties form the theoretical foundation for database consistency and reliability. Atomicity requires that a transaction must be treated as a single, indivisible unit - it either completes entirely or has no effect at all. Consistency ensures that a transaction can only transition the database from one valid state to another, preserving all defined rules and constraints. Isolation mandates that concurrent transactions execute as if they were running sequentially, preventing interference between operations. Durability guarantees that once a transaction is committed, its changes will persist even in the case of system failures.

The concept of "fitness for use" provides a framework for evaluating whether a system can reliably serve its intended purpose (Wang & Strong, 1996). While some applications can tolerate partial degradation while remaining functional, certain systems - like banking, telecommunications, and voter registration databases - require complete data integrity. In such zero-trust environments, where stakeholders require absolute confidence in system outputs, any unresolvable data inconsistencies render the system unfit for use.

The documented violations of these principles in voter registration systems - such as extensive record duplication and irreconcilable inter-database disparities - indicate fundamental integrity issues that prevent the system from performing its core functions. These issues create mathematical uncertainties that cannot be resolved through standard auditing procedures, regardless of their original causes.

2. Methodology

This study presents findings from an ongoing multi-state analysis of voter registration system reliability. The investigation employs three complementary analytical approaches: systemic pattern detection, cross-database validation, and document verification. Rather than attempting to determine causes, the methodology focuses solely on identifying and validating reliability issues that prevent these systems from performing their core functions.

Pattern detection begins with systematic examination of voter registration databases, focusing on three key areas: record integrity, ID number distribution, and algorithmic patterns. Record integrity assessment examines duplicate records, registration dates, and field consistency. ID number analysis evaluates distribution patterns and relationships between state and county identifiers. Algorithmic pattern detection identifies systematic variations from expected random or sequential numbering.

Findings undergo multiple validation steps to ensure accuracy. Internal validation includes statistical testing where appropriate, cross-referencing of multiple data fields, and verification through alternative analytical approaches. External validation compares patterns across different jurisdictions and validates against established database management principles. For documentary evidence, such as registration forms and signatures, physical examination provides additional verification.

The analysis encompasses several primary data sources, including state voter registration databases, county-level registration records, and historical database versions. Access to specific data types varies by jurisdiction, creating methodological constraints that shape analytical depth. While some jurisdictions provided comprehensive data access, others limited available fields or historical records. The methodology adapts to these constraints while maintaining consistent baseline analyses that enable cross-state comparison where appropriate.

Key limitations include:

- Variable data access across jurisdictions
- Inconsistent historical record availability
- Database size constraints on analysis
- System documentation gaps
- Time constraints on pattern validation

The methodology emphasizes reproducible analysis techniques while maintaining analytical neutrality regarding causation. This approach allows for systematic identification and validation of reliability issues across different jurisdictions, even with varying data availability.

3. Evidence

This analysis presents four intersecting categories of evidence that demonstrate fundamental reliability failures in state voter registration systems. First, systematic analysis reveals widespread unauthorized record duplication, with millions of duplicate IDs persisting across multiple election cycles. Second, cross-database reconciliation attempts expose mathematical impossibilities between state and county records that cannot be explained by normal administrative processes. Third, examination of registration documents shows physically impossible duplicated signatures across multiple active voter IDs. Finally, sophisticated algorithms discovered across multiple states enable systematic record manipulation while bypassing normal database controls.

Before examining these categories in detail, historical analysis of clone records across states provides crucial context for understanding these system failures.

3.1 Clone Registration Growth Patterns Across States

A comparative analysis of voter registration records from 1990-2024 reveals two distinct patterns of system compromise. The New York pattern demonstrates progressive degradation from an initially functional state, while the Georgia pattern suggests a system that likely never achieved basic data integrity (Paquette, 2024c).

New York's progression shows clear evidence that clone-free operation is technically possible (Table 1). Starting from near-zero clone rates (0.25% in 1990), the system experienced systematic degradation:

- 1990-1995: Below 2%
- 1996-2000: Increased to 3-4% range
- 2001-2006: Climbed to 5-6%
- 2007-2015: Rose to 8-12%
- 2016-2022: Escalated to 13-17%

Table 1: Clone growth by year, NY state, 1990-2022

| | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 |
|----------------|---------|-----------|---------|---------|---------|---------|---------|---------|---------|-----------|---------|---------|---------|-----------|-----------|---------|---------|
| Clones | 514 | 925 | 4,699 | 1,896 | 5,792 | 6,202 | 13,185 | 9,171 | 11,790 | 14,705 | 27,442 | 16,114 | 19,605 | 21,667 | 56,262 | 19,059 | 21,840 |
| Total | 206,895 | 270,123 | 844,021 | 312,375 | 336,611 | 471,808 | 797,165 | 439,670 | 368,352 | 375,976 | 710,394 | 388,004 | 419,772 | 406,860 | 1,008,143 | 323,087 | 373,464 |
| Percent Clones | 0.25% | 0.34% | 0.56% | 0.61% | 1.72% | 1.31% | 1.65% | 2.09% | 3.20% | 3.91% | 3.86% | 4.15% | 4.67% | 5.33% | 5.58% | 5.90% | 5.85% |
| | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | |
| Clones | 34,893 | 99,556 | 33,377 | 43,487 | 42,266 | 101,843 | 43,941 | 46,448 | 45,660 | 177,523 | 56,832 | 86,765 | 75,090 | 178,755 | 59,354 | 87,626 | |
| Total | 391,201 | 1,150,253 | 333,032 | 379,390 | 350,186 | 908,300 | 383,187 | 380,551 | 434,755 | 1,191,531 | 380,659 | 687,298 | 574,203 | 1,130,608 | 454,017 | 504,868 | |
| Percent Clones | 8.92% | 8.66% | 10.02% | 11.46% | 12.07% | 11.21% | 11.47% | 12.21% | 10.50% | 14.90% | 14.93% | 12.62% | 13.08% | 15.81% | 13.07% | 17.36% | |

In contrast, Georgia maintained consistently high clone rates (6-8%) over multiple decades, a pattern also seen in Arizona (Table 2). While this stability might appear preferable to New York's increasing rates, it actually represents a more concerning scenario - these systems likely never achieved basic data integrity.

Table 2: Clone growth by year, Georgia, 1990-2024

| | <1990 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 |
|------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Clones | 31,607 | 3,270 | 1,651 | 8,959 | 1,501 | 5,386 | 5,892 | 8,934 | 3,992 | 5,168 | 3,876 | 8,735 |
| Total | 394,287 | 38,822 | 19,735 | 107,032 | 17,587 | 64,044 | 71,563 | 109,418 | 50,672 | 65,010 | 51,806 | 112,583 |
| Pct Clones | 8.02% | 8.42% | 8.36% | 8.37% | 8.53% | 8.41% | 8.23% | 8.16% | 7.88% | 7.95% | 7.48% | 7.76% |
| | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| Clones | 3,875 | 5,645 | 5,726 | 13,482 | 6,415 | 8,391 | 8,515 | 18,631 | 5,082 | 7,533 | 7,482 | 16,815 |
| Total | 51,480 | 74,848 | 77,656 | 174,821 | 85,535 | 116,584 | 117,284 | 245,209 | 70,705 | 106,053 | 106,818 | 239,711 |
| Pct Clones | 7.53% | 7.54% | 7.37% | 7.71% | 7.50% | 7.20% | 7.26% | 7.60% | 7.19% | 7.10% | 7.00% | 7.01% |
| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
| Clones | 7,796 | 12,395 | 10,538 | 30,959 | 23,834 | 35,005 | 30,246 | 44,785 | 17,490 | 32,159 | 25,682 | 22,116 |
| Total | 115,661 | 181,888 | 164,142 | 461,959 | 360,224 | 527,839 | 470,504 | 691,020 | 281,128 | 552,869 | 465,976 | 377,385 |
| Pct Clones | 6.74% | 6.81% | 6.42% | 6.70% | 6.62% | 6.63% | 6.43% | 6.48% | 6.22% | 5.82% | 5.51% | 5.86% |

Most states follow New York's pattern of increasing clone rates, with two distinct acceleration periods: one in the mid-1990s and another, more dramatic increase in the early 2000s. These system-wide changes affected multiple states simultaneously, suggesting broad structural shifts rather than isolated anomalies (Paquette, 2024d).

3.2 Record Duplication: Systematic Analysis

3.2.1 Definitional framework

The analysis distinguishes between duplicate records (identical in all fields) and clone records (sharing core identifying traits while varying in other fields). Clone records represent a more significant system reliability issue as each possesses a unique voter ID number, enabling independent function within the voting system. Under HAVA Section 303(a)(1)(A), the presence of multiple unique identifiers for a single voter constitutes an illegal multiple registration, distinct from harmless duplicate records.

3.2.2 Legal controls and system requirements

State and federal regulations establish specific validation protocols to prevent multiple registrations. For instance, New York law mandates a systematic verification process using:

- Primary matching: first name, last name, and date of birth
- Secondary validation: driver's license or last four SSN digits When these matches occur, the system should prevent the creation of a new voter ID, making clone record creation technically impossible under compliant operations.

3.2.3 Cross-State analysis findings

Systematic analysis across multiple state databases revealed significant clone record populations:

Major System Anomalies:

- New York: 1.47 million excess voter IDs (6.9% of 21.37M total records)
- Wisconsin: 437,228 minimum estimated clones (5.6% of 7.74M total) (Paquette, 2024h)
- Arizona: 590,530 minimum estimated clones (8.6% of 6.85M total) (Paquette, 2024a)
- Georgia: 588,323 minimum estimated clones (8.1% of 7.22M total)

Moderate System Anomalies:

- Texas: 57,952 confirmed excess IDs (0.3% of 18.38M total) (Paquette, 2024g)
- Pennsylvania: 9,947 excess IDs (0.1% of 8.85M total) (Paquette, 2024f)
- New Jersey: 9,105 excess IDs (0.1% of 6.46M total) (Paquette, 2025)

The scale and consistency of these findings across multiple jurisdictions indicates a systemic reliability issue rather than isolated anomalies or technical limitations. This pattern of clone records fundamentally compromises the system's ability to maintain unique voter identification - a core functional requirement for electoral record integrity.

Analysis reveals specific, mathematically verifiable correlations between certain ID patterns and clone records. In New York's Shingle algorithm records, for example, clone status can be predicted with high accuracy in the upper range of County ID numbers, where nearly 100% are clones. However, such predictive capability varies significantly by algorithm and ID range, and cannot be generalized across all records. The key finding is not the ability to identify individual clones, but rather the existence of systematic patterns that should not appear in properly functioning voter registration systems.

3.3 Cross-Database Reconciliation Failures in New York

Analysis of New York's state and county voter registration databases revealed systemic reconciliation failures that fundamentally compromise the system's ability to provide accurate voter participation records. In New York City's five counties (Bronx, Kings, Queens, New York, and Richmond), 254,713 voter ID numbers show 2020 General Election participation in county records but no corresponding vote in state records. These discrepancies persist in databases generated well after the election, eliminating timing differences as a potential explanation.

Further analysis revealed 225,517 voter IDs containing multiple recorded votes for the 2020 General Election, with different voting methods indicated for each instance (e.g., early voting and in-person voting for the same ID). The majority of these multiple vote histories - 206,205 cases - are concentrated in Nassau County. Notably, these duplicate votes were absent from the database dated 10/20/2021 but appeared in the 12/22/2022 version, indicating retroactive modification of historical voting records.

Vote count reconciliation across different reporting systems reveals additional mathematical inconsistencies. While certified results show 3,039,376 total votes across NYC's five counties, the state database records only 2,804,872 votes, and county databases show 2,878,108 votes. The county number is particularly interesting because the counties didn't provide purged records but the state did. This would suggest a higher state count due to purged records at the county level, not the reverse.

Individual county disparities are particularly stark - the Bronx shows 425,883 certified votes but only 382,672 in state records, while Richmond County reports 216,278 certified votes compared to 172,350 in state records. In Queens County a count of voters who voted that compares ID numbers, reveals 55,055 votes missing from state records (Table 3). These discrepancies are not merely clerical variations; they represent fundamental inconsistencies in how votes are recorded and tracked across different parts of the system.

Table 3: Missing 2020 GE votes, Queens County, NY based on matching ID numbers

| | Certified | Precincts | State | County | Diff S/C | State only | County only |
|------------|-----------|-----------|---------|---------|----------|------------|-------------|
| Count | 788,262 | 789,973 | 737,986 | 739,885 | 1,899 | 8 | 55,063 |
| Matching | | | 737,978 | 684,822 | 53,156 | | |
| Difference | | | 8 | 55,063 | 55,055 | | |

These findings demonstrate critical database reliability issues that prevent accurate determination of voter participation. The presence of irreconcilable vote histories for identical voter IDs, significant variations in vote totals between state and county systems, and evidence of retroactive record modifications create mathematical uncertainties that cannot be resolved through standard auditing procedures (Table 4).

Table 4: Example individual record, missing vote in state records and double vote despite purged status

| 6 | State | County | State | County |
|-------------|---|-------------|-------------|---------|
| CID | 413,748,568 | 413,748,568 | 413,757,275 | NYC/no |
| SBOEID | 58,924,130 | | 58,949,450 | county |
| Type | Orig | Orig | Clone | purged |
| RegDate | 6/23/2020 | 6/23/2020 | 6/23/2020 | records |
| Status | Active | Active | Purged | Purged |
| PurgeDate | NONE | NONE | 1/26/2021 | |
| First N | Nora | Nora | Nora | |
| Last N | Antwi | Antwi | Antwi | |
| DOB | 4/2/2002 | 4/2/2002 | 4/2/2002 | |
| Elec Date | NONE | 11/3/2020 | 11/3/2020 | NONE |
| Res NUM | 905 | 905 | 905 | |
| Res Street | Summit Ave | Summit Ave | Summit Ave | |
| City | Bronx | Bronx | Bronx | |
| County | Bronx | Bronx | Bronx | |
| Explanation | This person has same RegDate/address clone. Clone is purged after voting in 2020. Double vote. County vote for original missing from state. | | | |

3.4 Document Authentication Failures

Examination of original registration documents reveals fundamental issues with record authentication that extend beyond simple database inconsistencies. In cases where county boards of elections provided registration documents in response to FOIL requests, clone records frequently contained photographically identical signatures despite having different voter ID numbers and remaining simultaneously active through multiple election cycles. This signature duplication definitively proves these are not independent registration applications, as it is physically impossible for a person to produce exactly identical handwritten signatures on separate occasions.

The time dimension of these findings is particularly significant. While clone records were typically purged shortly after FOIL requests brought them to official attention, many had remained simultaneously active in the system for years. For example, the Herkimer County cases show identical-signature clone records that remained active from their 2020 creation until 2022, spanning multiple elections. These records were only marked as duplicates after external inquiry, indicating a systemic failure of internal auditing processes.

This pattern of findings from smaller counties that cooperated with records requests raises serious concerns about larger jurisdictions that did not provide documentation. The counties with the highest numbers of identified clone records - New York City's five counties and Nassau County - declined to provide registration documents for examination. Given that proof of unauthorized record duplication was found in most smaller counties that provided records, the implications for jurisdictions with hundreds of thousands of potential clones are significant.

The authentication crisis extends beyond database anomalies to the fundamental relationship between electronic records and their paper documentation. Voter registration systems rely on original signed documents as the authoritative source for voter records. When electronic records show impossible duplications of original signatures while maintaining separate active voter IDs, it compromises the entire chain of documentation needed for registration verification. This creates an irreconcilable situation where neither the electronic records nor their paper documentation can be relied upon to determine legitimate voter registrations.

3.5 Registration Date Patterns

A critical anomaly emerged in California's District 28 when 60,376 voter records suddenly appeared during the vote counting period between November 10-15, 2024 (Paquette, 2024b). These records exhibited an unnaturally perfect distribution of registration dates spanning 124 years, from 1900 to present. The temporal distribution appeared statistically natural at first glance - showing minimal activity through the 1970s, increasing volume through the 1980s (3,467) and 1990s (7,459), peaking in the 2000s (10,699) and 2010s (21,679), with 16,521 from 2020 forward. However, the records appeared sometime within a narrow five day period in 2024. The

appearance of such precisely distributed historical registrations during active vote counting raises serious concerns about data manipulation.

3.6 Record Disappearance

In Ohio, a comparison between 2020 and 2024 databases revealed an alarming pattern of record disappearance in Cuyahoga County. Of 172,201 voters registered between January-October 2020, only 96,397 remained in the 2024 database - meaning 75,804 records (44.02%) vanished in less than four years. This pattern defies normal administrative processes, as Ohio requires a minimum of four years of inactivity before records can be marked inactive, let alone deleted. The scale of deletion cannot be explained by normal factors like death or relocation, particularly given the short timeframe and the fact these were all recently registered voters.

3.7 Activity and Status Issues

The Ohio analysis revealed systemic problems with voter activity tracking. In District 28, out of 397,828 total records, 126,302 showed no voting activity across all three federal elections from 2020-2024. While 4,680 of these were registered after 2019, the remaining 121,622 records showed no activity despite being registered before 2020. Under federal and state voter list maintenance laws, these inactive records should have been flagged for removal after missing two federal elections. Their continued presence as active records, particularly through three consecutive federal election cycles, represents a clear deviation from statutory requirements for maintaining voter roll accuracy.

These patterns share a common theme: they represent deviations from both statistical probability and legal requirements that cannot be explained through normal administrative processes or human behavior. The mathematical precision in some cases, and the scale of unexplained discrepancies in others, suggests systematic manipulation rather than random error or normal database maintenance activities.

These distinct patterns of clone record generation across states provide essential context for understanding the systematic mechanisms revealed through ID number analysis, discussed in the next section.

4. Systematic Mechanisms

A pervasive finding across all but one of the ten states examined, (Oklahoma) (Paquette, 2024e), is the presence of sophisticated ID number assignment systems that go far beyond standard database requirements. These systems create mathematically predictable relationships between IDs that enable specific capabilities while raising significant reliability concerns.

In New York (Paquette, 2023), three distinct algorithms demonstrate different aspects of system vulnerability:

1. The Spiral algorithm mathematically transforms relationships between County IDs (CID) and State Board of Elections IDs (SBOEID) using a base-10 repunit structure (Table 5). Analysis proves this creates a third, derivable identifier (AID) through CID-SBOEID mapping. While this mathematical capability suggests possible linkage to undocumented record systems, such links cannot be proven from available data.
2. The Shingle algorithm shows specific, provable correlations with clone records in certain ID ranges. In the upper 50% of CID numbers, nearly 100% of records are clones, while lower ranges show approximately 20% clone rates. This creates mathematically predictable patterns within a defined subset of records.
3. The Tartan algorithm contains the majority of clone records and coincides temporally with increased clone rates starting in 2007. While this correlation is clear, causation cannot be established from available data.

Similar mathematical patterns appear across multiple states. New Jersey implements reversible number transformations that can encode additional data channels. Texas uses an intricate modulus-8 system with layered patterns (Table 6). Ohio employs similar mathematical structures but only in three counties (Table 7).

These systems demonstrably enable:

- Mathematical frameworks for hidden record attributes
- Predictable relationships between certain ID types
- Recovery of deleted records through ID relationships (in specific cases)
- Record segregation by mathematical properties

The sophistication and similarities of these systems across states indicates deliberate design rather than administrative error. While specific uses cannot be proven in most cases, these mechanisms fundamentally compromise system transparency and reliability by creating mathematical capabilities that bypass normal database controls.

Table 5: Example Spiral algorithm details, organized by power of 10 columns (1, 11, 111, 1,111)

| Short ID | SBOEID Gap | CID Alpha | CID Num | Reg Date RF | Short ID | SBOEID Gap | CID Num | Reg Date RF | Short ID | SBOEID Gap | CID Num | Reg Date RF | Short ID | SBOEID Gap | CID Num | Reg Date RF |
|------------|------------|-----------|---------|-------------|------------|------------|-----------|-------------|------------|------------|---------|-------------|------------|------------|---------|-------------|
| 20,462,690 | 122,587 | A | 54,878 | 06/14/1996 | 20,462,697 | 122,577 | 1,014,135 | 07/25/2000 | 20,462,772 | 122,477 | 29,057 | 10/14/1967 | 20,463,522 | 121,477 | 21,766 | 10/02/1971 |
| 20,462,691 | 1 | A | 54,879 | 06/17/1996 | 20,462,708 | 11 | 1,014,136 | 07/25/2000 | 20,462,883 | 111 | 29,132 | 10/06/1975 | 20,464,633 | 1,111 | 21,796 | 10/02/1972 |
| 20,462,692 | 1 | A | 54,880 | 06/14/1996 | 20,462,719 | 11 | 1,014,137 | 07/25/2000 | 20,462,994 | 111 | 29,141 | 10/15/1977 | 20,465,744 | 1,111 | 21,812 | 10/02/1972 |
| 20,462,693 | 1 | A | 54,881 | 06/14/1996 | 20,462,730 | 11 | 1,014,138 | 07/25/2000 | 20,463,105 | 111 | 29,148 | 10/15/1977 | 20,466,855 | 1,111 | 21,815 | 10/02/1972 |
| 20,462,694 | 1 | A | 54,883 | 06/14/1996 | 20,462,741 | 11 | 1,014,139 | 07/25/2000 | 20,463,216 | 111 | 29,154 | 10/02/1976 | 20,467,966 | 1,111 | 21,816 | 10/02/1972 |
| 20,462,695 | 1 | A | 54,885 | 06/14/1996 | 20,462,752 | 11 | 1,014,140 | 07/25/2000 | 20,463,327 | 111 | 29,174 | 10/02/1976 | 20,469,077 | 1,111 | 21,849 | 10/02/1972 |
| 20,462,696 | 1 | A | 54,887 | 06/14/1996 | 20,462,763 | 11 | 1,014,142 | 07/25/2000 | 20,463,438 | 111 | 29,175 | 10/02/1976 | 20,470,188 | 1,111 | 21,855 | 10/02/1972 |
| 20,462,698 | 2 | A | 54,888 | 06/14/1996 | 20,462,775 | 12 | 1,014,143 | 07/25/2000 | 20,463,550 | 112 | 29,182 | 10/02/1976 | 20,471,300 | 1,112 | 21,866 | 10/10/1972 |
| 20,462,699 | 1 | A | 54,890 | 06/14/1996 | 20,462,786 | 11 | 1,014,144 | 07/25/2000 | 20,463,661 | 111 | 29,187 | 10/02/1976 | 20,472,411 | 1,111 | 21,873 | 10/11/1973 |
| 20,462,700 | 1 | A | 54,891 | 06/14/1996 | 20,462,797 | 11 | 1,014,146 | 07/25/2000 | 20,463,772 | 111 | 29,191 | 10/02/1976 | 20,473,522 | 1,111 | 21,874 | 10/11/1973 |
| 20,462,701 | 1 | A | 54,893 | 06/14/1996 | 20,462,808 | 11 | 1,014,147 | 07/25/2000 | 20,463,883 | 111 | 29,219 | 09/28/1974 | 20,474,633 | 1,111 | 21,879 | 10/13/1973 |
| 20,462,702 | 1 | A | 54,895 | 06/14/1996 | 20,462,819 | 11 | 1,014,148 | 07/25/2000 | 20,463,994 | 111 | 29,223 | 09/28/1974 | 20,475,744 | 1,111 | 21,884 | 09/28/1974 |
| 20,462,703 | 1 | A | 54,898 | 06/14/1996 | 20,462,830 | 11 | 1,014,149 | 07/25/2000 | 20,464,105 | 111 | 29,261 | 10/05/1976 | 20,476,855 | 1,111 | 21,898 | 10/04/1975 |
| 20,462,704 | 1 | A | 54,901 | 06/17/1996 | 20,462,841 | 11 | 1,014,150 | 07/25/2000 | 20,464,216 | 111 | 29,263 | 10/15/1977 | 20,477,966 | 1,111 | 21,901 | 10/04/1975 |
| 20,462,705 | 1 | A | 54,902 | 06/17/1996 | 20,462,852 | 11 | 1,014,151 | 07/25/2000 | 20,464,327 | 111 | 29,266 | 10/11/1980 | 20,479,077 | 1,111 | 21,933 | 10/15/1977 |
| 20,462,706 | 1 | A | 54,905 | 06/17/1996 | 20,462,863 | 11 | 1,014,152 | 07/25/2000 | 20,464,438 | 111 | 29,276 | 10/11/1980 | 20,480,188 | 1,111 | 21,943 | 09/29/1979 |
| 20,462,707 | 1 | A | 54,907 | 06/17/1996 | 20,462,874 | 11 | 1,014,153 | 07/25/2000 | 20,464,549 | 111 | 29,278 | 10/16/1982 | 20,481,299 | 1,111 | 21,951 | 10/10/1981 |
| 20,462,709 | 2 | A | 54,908 | 06/17/1996 | 20,462,886 | 12 | 1,014,155 | 07/25/2000 | 20,464,661 | 112 | 29,361 | 10/11/1980 | 20,482,411 | 1,112 | 21,954 | 10/10/1981 |
| 20,462,710 | 1 | A | 54,909 | 06/17/1996 | 20,462,897 | 11 | 1,014,156 | 07/25/2000 | 20,464,772 | 111 | 29,362 | 10/11/1980 | 20,483,522 | 1,111 | 21,955 | 10/10/1981 |
| 20,462,711 | 1 | A | 54,912 | 06/17/1996 | 20,462,908 | 11 | 1,014,157 | 07/25/2000 | 20,464,883 | 111 | 29,363 | 10/11/1980 | 20,484,633 | 1,111 | 21,956 | 10/16/1982 |
| 20,462,712 | 1 | A | 54,914 | 06/17/1996 | 20,462,919 | 11 | 1,014,158 | 07/25/2000 | 20,464,994 | 111 | 29,365 | 10/11/1980 | 20,485,744 | 1,111 | 21,957 | 10/16/1982 |
| 20,462,713 | 1 | A | 54,916 | 06/18/1996 | 20,462,930 | 11 | 1,014,162 | 07/25/2000 | 20,465,105 | 111 | 29,369 | 10/11/1980 | 20,486,855 | 1,111 | 22,016 | 10/03/1967 |
| 20,462,714 | 1 | A | 54,917 | 06/18/1996 | 20,462,941 | 11 | 1,014,163 | 07/25/2000 | 20,465,216 | 111 | 29,381 | 10/11/1980 | 20,487,966 | 1,111 | 22,018 | 10/03/1967 |
| 20,462,715 | 1 | A | 54,918 | 06/18/1996 | 20,462,952 | 11 | 1,014,164 | 07/25/2000 | 20,465,327 | 111 | 29,388 | 10/10/1981 | 20,489,077 | 1,111 | 22,023 | 10/03/1967 |
| 20,462,716 | 1 | A | 54,919 | 06/18/1996 | 20,462,963 | 11 | 1,014,165 | 07/25/2000 | 20,465,438 | 111 | 29,391 | 10/10/1981 | 20,490,188 | 1,111 | 22,035 | 10/03/1967 |
| 20,462,717 | 1 | A | 54,920 | 06/18/1996 | 20,462,974 | 11 | 1,014,166 | 07/25/2000 | 20,465,549 | 111 | 29,392 | 10/10/1981 | 20,491,300 | 1,112 | 22,040 | 10/03/1967 |
| 20,462,718 | 1 | A | 54,921 | 06/18/1996 | 20,462,985 | 11 | 1,014,170 | 07/25/2000 | 20,465,660 | 111 | 29,403 | 10/15/1983 | 20,492,411 | 1,111 | 22,050 | 10/03/1967 |
| 20,462,720 | 2 | A | 54,922 | 06/18/1996 | 20,462,997 | 12 | 1,014,172 | 07/26/2000 | 20,465,772 | 112 | 29,405 | 10/15/1983 | 20,493,523 | 1,112 | 22,061 | 10/03/1967 |

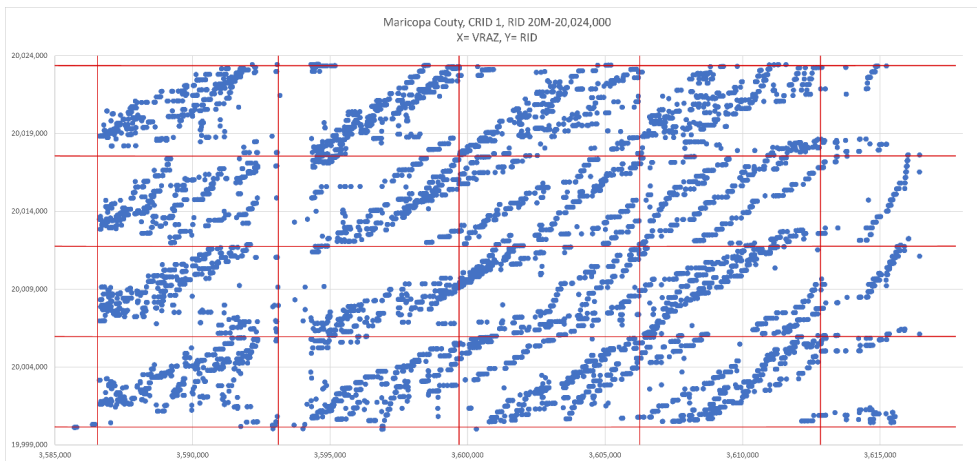


Figure 1: Maricopa County, AZ Braid pattern closeup shows cyclic pattern similar to NY's Shingle

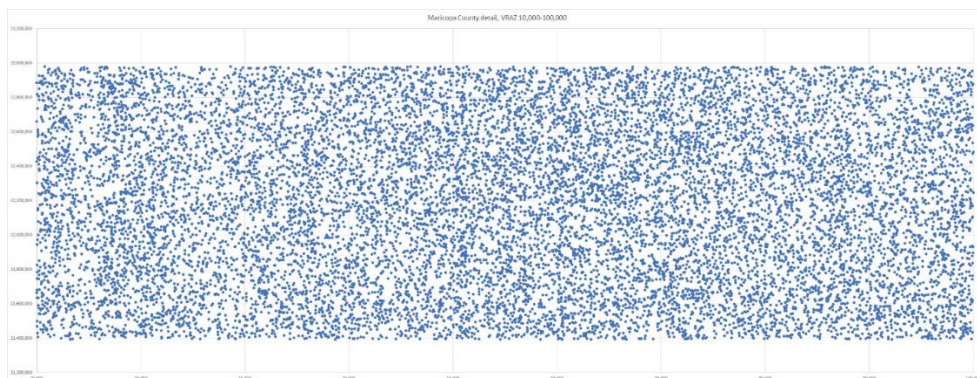


Figure 2: Detail, Arizona's Metronome Pattern, Maricopa County

Table 6: Harris County, TX Modulo /8 ID number pattern

| Mod 0 | Freq Mod 0 | Mod 1 | Freq Mod 1 | Mod 2 | Freq Mod 2 | Mod 3 | Freq Mod 3 | Mod 4 | Freq Mod 4 | Mod 5 | Freq Mod 5 | Mod 6 | Freq Mod 6 | Mod 7 | Freq Mod 7 |
|-------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|------------|
| 8 | 167106 | 1 | 0 | 2 | 0 | 3 | 1 | 4 | 6 | 5 | 121 | 6 | 1253 | 7 | 16477 |
| 16 | 79230 | 9 | 0 | 10 | 0 | 11 | 0 | 12 | 4 | 13 | 104 | 14 | 1224 | 15 | 16777 |
| 24 | 34619 | 17 | 7066 | 18 | 41933 | 19 | 0 | 20 | 0 | 21 | 21 | 22 | 629 | 23 | 11058 |
| 32 | 12725 | 25 | 16766 | 26 | 52266 | 27 | 0 | 28 | 0 | 29 | 1 | 30 | 48 | 31 | 4006 |
| 40 | 3213 | 33 | 25558 | 34 | 48868 | 35 | 0 | 36 | 0 | 37 | 2 | 38 | 27 | 39 | 334 |
| 48 | 2370 | 41 | 32521 | 42 | 40629 | 43 | 0 | 44 | 0 | 45 | 0 | 46 | 13 | 47 | 228 |
| 56 | 1130 | 49 | 30638 | 50 | 30705 | 51 | 0 | 52 | 0 | 53 | 5 | 54 | 55 | 55 | 594 |
| 64 | 516 | 57 | 21985 | 58 | 15859 | 59 | 3410 | 60 | 0 | 61 | 1 | 62 | 36 | 63 | 524 |
| 72 | 256 | 65 | 14284 | 66 | 7539 | 67 | 9269 | 68 | 3811 | 69 | 0 | 70 | 1 | 71 | 190 |
| 80 | 188 | 73 | 8598 | 74 | 3113 | 75 | 13816 | 76 | 4467 | 77 | 0 | 78 | 0 | 79 | 15 |
| 88 | 190 | 81 | 3858 | 82 | 970 | 83 | 17425 | 84 | 3682 | 85 | 0 | 86 | 4 | 87 | 13 |
| 96 | 152 | 89 | 1831 | 90 | 236 | 91 | 20287 | 92 | 2004 | 93 | 0 | 94 | 0 | 95 | 14 |
| 104 | 151 | 97 | 1435 | 98 | 43 | 99 | 18774 | 100 | 0 | 101 | 0 | 102 | 0 | 103 | 12 |
| 112 | 107 | 105 | 881 | 106 | 1118 | 107 | 11111 | 108 | 0 | 109 | 2095 | 110 | 0 | 111 | 5 |
| 120 | 2 | 113 | 471 | 114 | 1395 | 115 | 6596 | 116 | 719 | 117 | 4694 | 118 | 0 | 119 | 0 |
| 128 | 6 | 121 | 182 | 122 | 1077 | 123 | 3552 | 124 | 1762 | 125 | 5609 | 126 | 0 | 127 | 0 |
| 136 | 5 | 129 | 48 | 130 | 484 | 131 | 1690 | 132 | 3019 | 133 | 5855 | 134 | 0 | 135 | 2 |
| 144 | 2 | 137 | 45 | 138 | 418 | 139 | 948 | 140 | 4382 | 141 | 5293 | 142 | 0 | 143 | 0 |
| 152 | 1 | 145 | 36 | 146 | 346 | 147 | 646 | 148 | 3896 | 149 | 3869 | 150 | 0 | 151 | 0 |
| 160 | 0 | 153 | 38 | 154 | 277 | 155 | 405 | 156 | 3121 | 157 | 2285 | 158 | 948 | 159 | 397 |
| 168 | 0 | 161 | 7 | 162 | 151 | 163 | 194 | 164 | 2412 | 165 | 1327 | 166 | 1890 | 167 | 875 |
| 176 | 0 | 169 | 0 | 170 | 9 | 171 | 121 | 172 | 1668 | 173 | 672 | 174 | 2854 | 175 | 946 |
| 184 | 0 | 177 | 1 | 178 | 4 | 179 | 85 | 180 | 180 | 181 | 294 | 182 | 3899 | 183 | 793 |
| 192 | 0 | 185 | 1 | 186 | 5 | 187 | 90 | 188 | 188 | 189 | 118 | 190 | 4837 | 191 | 479 |
| 200 | 0 | 193 | 0 | 194 | 3 | 195 | 60 | 196 | 653 | 197 | 40 | 198 | 3894 | 199 | 12 |

Table 7: Franklin County, OH Modulo 8 ID number pattern is a vertical mirror image of Harris, TX

| Group A Gap | Group A Frequency y | Group B Gap | Group B Frequency y | Group C Gap | Group C Frequency y | Group D Gap | Group D Frequency y | Group E Gap | Group E Frequency y | Group F Gap | Group F Frequency y | Group G Gap | Group G Frequency y | Group H Gap | Group H Frequency y |
|-------------|---------------------|-------------|---------------------|-------------|---------------------|-------------|---------------------|-------------|---------------------|-------------|---------------------|-------------|---------------------|-------------|---------------------|
| 1 | 0 | 2 | 0 | 3 | 1456 | 4 | 29 | 5 | 0 | 6 | 0 | 7 | 353 | 8 | 38771 |
| 9 | 377 | 10 | 0 | 11 | 623 | 12 | 41 | 13 | 34 | 14 | 2883 | 15 | 314 | 16 | 16865 |
| 17 | 285 | 18 | 414 | 19 | 4800 | 20 | 0 | 21 | 22 | 22 | 5423 | 23 | 213 | 24 | 7347 |
| 25 | 235 | 26 | 538 | 27 | 9930 | 28 | 19 | 29 | 0 | 30 | 7578 | 31 | 84 | 32 | 2535 |
| 33 | 160 | 34 | 670 | 35 | 10234 | 36 | 33 | 37 | 0 | 38 | 6296 | 39 | 71 | 40 | 0 |
| 41 | 99 | 42 | 801 | 43 | 9796 | 44 | 56 | 45 | 0 | 46 | 4545 | 47 | 79 | 48 | 72 |
| 49 | 723 | 50 | 935 | 51 | 8295 | 52 | 82 | 53 | 0 | 54 | 3005 | 55 | 87 | 56 | 87 |
| 57 | 2552 | 58 | 639 | 59 | 5303 | 60 | 146 | 61 | 0 | 62 | 1401 | 63 | 84 | 64 | 67 |
| 65 | 4158 | 66 | 429 | 67 | 2528 | 68 | 100 | 69 | 130 | 70 | 0 | 71 | 73 | 72 | 84 |
| 73 | 5427 | 74 | 293 | 75 | 1003 | 76 | 97 | 77 | 303 | 78 | 825 | 79 | 7 | 80 | 77 |
| 81 | 6491 | 82 | 110 | 83 | 256 | 84 | 47 | 85 | 388 | 86 | 812 | 87 | 23 | 88 | 0 |
| 89 | 6132 | 90 | 83 | 91 | 8 | 92 | 22 | 93 | 464 | 94 | 501 | 95 | 33 | 96 | 0 |
| 97 | 4373 | 98 | 73 | 99 | 83 | 100 | 8 | 101 | 576 | 102 | 2 | 103 | 35 | 104 | 43 |
| 105 | 2340 | 106 | 61 | 107 | 76 | 108 | 1389 | 109 | 441 | 110 | 13 | 111 | 498 | 112 | 39 |
| 113 | 1051 | 114 | 60 | 115 | 131 | 116 | 1978 | 117 | 230 | 118 | 5 | 119 | 715 | 120 | 18 |
| 121 | 280 | 122 | 39 | 123 | 171 | 124 | 2221 | 125 | 148 | 126 | 4 | 127 | 754 | 128 | 69 |
| 129 | 14 | 130 | 3 | 131 | 240 | 132 | 2211 | 133 | 81 | 134 | 3 | 135 | 594 | 136 | 132 |
| 137 | 12 | 138 | 204 | 139 | 257 | 140 | 1977 | 141 | 37 | 142 | 4 | 143 | 332 | 144 | 144 |
| 145 | 17 | 146 | 515 | 147 | 195 | 148 | 1177 | 149 | 62 | 150 | 0 | 151 | 128 | 152 | 137 |
| 153 | 16 | 154 | 795 | 155 | 140 | 156 | 589 | 157 | 47 | 158 | 84 | 159 | 130 | 160 | 101 |
| 161 | 15 | 162 | 1006 | 163 | 75 | 164 | 228 | 165 | 25 | 166 | 139 | 167 | 274 | 168 | 53 |
| 169 | 0 | 170 | 1346 | 171 | 34 | 172 | 66 | 173 | 20 | 174 | 196 | 175 | 322 | 176 | 35 |
| 177 | 0 | 178 | 1011 | 179 | 27 | 180 | 0 | 181 | 15 | 182 | 194 | 183 | 288 | 184 | 33 |

4.1 Algorithmic Evidence

The algorithms reveal themselves through consistent mathematical patterns. New York's Spiral algorithm produces regular gaps of 1,111, 111, and 11 between ID numbers. Texas demonstrates modulus-8 based groupings with secondary modulus-99 patterns. New Jersey shows systematic number transformations that can be reversed to reveal original values. Cross-state analysis finds shared characteristics like modular arithmetic, number segregation, and hidden indexing systems. The algorithms enable both attribute tagging and recovery of deleted records through mathematical relationships.

4.2 Manipulation Capabilities

These systems enable several concerning capabilities:

- ID relationship control through algorithmic mapping of numbers
- Record segregation via mathematical grouping
- Data opacity through complex transformations
- Disruption of normal audit trails by obscuring record relationships
- Consistent patterns suggesting coordinated implementation

The systems allow covert record tracking while maintaining surface-level compliance with public database requirements. The sophistication and similarities across states indicate deliberate design rather than administrative error. Technical analysis reveals capabilities for:

- Creating hidden record attributes without visible database fields
- Recovering supposedly deleted records through ID relationships
- Segregating records by mathematical properties
- Obscuring relationships between related records
- Maintaining consistency across different implementations

The consistency of these patterns across multiple states, sophisticated mathematical foundations, and clear capabilities for covert record manipulation present significant concerns for the utility and reliability of these critical election infrastructure databases.

5. System Reliability Impacts

The algorithmic manipulation of voter identification numbers, combined with documented record anomalies, fundamentally compromises these voter registration systems' ability to perform their intended functions. Unlike systems that might be repaired or repurposed, the nature of these compromises precludes even basic reliability.

In standard database design, sequential ID assignment provides transparent chronological tracking, enables straightforward auditing, and ensures visible relationships between records. Most critically, it ensures one-to-one correspondence between voters and ID numbers. The algorithms discovered in these systems actively work against these requirements, creating ID assignments that deliberately obscure record relationships and enable the creation of duplicate records that appear unique under normal database operations.

This technical compromise creates cascading failures throughout the system. When state and county databases disagree on over 250,000 voter participation records while maintaining similar total counts through apparent vote reassignment, basic mathematical certainty is lost. Document authentication failures compound this weakness - the presence of identical signatures across multiple active registrations with different algorithmically-generated IDs means neither electronic records nor paper documentation can reliably verify legitimate registrations.

These systems demonstrably cannot:

- Uniquely identify individual voters
- Track voter participation accurately
- Maintain consistent historical records
- Enable effective auditing
- Prevent or detect duplicate registrations

For election administrators tasked with maintaining accurate voter rolls, these systems no longer provide a reliable foundation. The combination of algorithmically obscured relationships, cross-database inconsistencies, and compromised authentication creates a situation where even basic questions about voter eligibility and participation cannot be answered with certainty. This represents a fundamental failure that cannot be mitigated through procedural changes or partial repairs. Furthermore, the fundamental nature of these system compromises extends beyond observable failures to the core architecture of the systems themselves.

The presence of sophisticated ID algorithms creates fundamental reliability issues regardless of their intended purpose or actual use. In properly functioning voter registration systems, relationships between records should be transparent and traceable through standard database operations. These algorithms instead create:

- Mathematically provable capabilities for hidden attributes
- Demonstrable third-party ID generation (as in the Spiral algorithm's AID)
- Verifiable patterns of record segregation
- Recoverable relationships between supposedly deleted records

Even if never exploited, these capabilities mean the systems cannot provide the transparency and reliability required for their core functions. Just as a banking system with built-in capability to hide transactions would be considered unreliable regardless of whether that capability was used, these voter registration systems are fundamentally compromised by the mere presence of these mathematical frameworks.

6. Conclusion

The materiality standard in regulatory oversight provides a useful framework for assessing these findings. In financial systems, evidence of intentional manipulation or control system bypass is automatically considered

material, regardless of scale, because it compromises system integrity. Applied to voter registration systems, the sophisticated algorithmic manipulation of ID numbers documented here represents a material compromise of system integrity.

The presence of these algorithms alone would raise concerns, but the discovery of widespread clone records with algorithmically-coordinated ID assignments, systematic manipulation of birthdates, and retroactive modification of voting histories provides concrete evidence of active exploitation. The combination of deliberately engineered mechanisms for hiding and tracking records with proof of their use to create unauthorized duplicate registrations demonstrates comprehensive system compromise.

Based on this analysis, these voter registration systems cannot be reliably used for their intended purpose. The sophisticated mechanisms for manipulating record relationships have fundamentally compromised the systems' ability to provide trustworthy data about voter registration and participation. More critically, the existence of anomalies that should have been prevented by legally mandated data validation measures demonstrates that basic database integrity controls were either bypassed or never implemented. The only viable remedy is complete reconstruction using transparent, standard database practices that implement all legally required data validation measures and ensure full administrative visibility of authentic record relationships.

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