# Online Appendix The Future of Felon Disenfranchisement Reform: Evidence from the Campaign to Restore Voting Rights in Florida 

Michael Morse

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I.

CAMPAIGN Finance Records
The Division of Elections posted online the campaign finance activity for Floridians for a Fair Democracy, the political action committee advocating for Amendment 4. ${ }^{1}$ I downloaded and standardized the data. For example, all donations by the Bonderman family (Cale Bonderman, Django Bonderman, Zoe Bonderman, and Laurie Michaels), Simons family (Liz Simons and James Simons), and Beckenstein family (Anita Beckenstein and Josh Beckenstein) are reported together. Donations by any entity created or funded by Tides (Tides Center, Tides Foundation, Alliance for Safety and Justice, and the Florida Restoration Rights Coalition) are also reported together.

II.<br>Petitions

## A. Data Collection

I made a public information request to the supervisor of elections of each county for the valid ballot petitions collected and submitted by the campaign.

1. That data is available at Campaign Finance Database, Fla. Dep't of State, Div. of ELECTIONS, https://dos.myflorida.com/elections/candidates-committees/campaign-finance/campaign-finance-database/ (select "contribution records" or "expenditure records," specify the "election year" as 2018, and search for the committee name "Floridians for a Fair Democracy").

Figure A. 1 provides an example of the petition forms that the campaign collected. I ultimately collected petition data from all sixty-seven counties in Florida.

Figure A.1: Example of Ballot Petition

## CONSTITUTIONAL AMENDMENT PETITION FORM

$$
\begin{array}{|l}
\hline \text { Note: } \\
\text { - All information on this form, including your signature, becomes a public record upon receipt by the Supervisor of Ele ctions } \\
\text { - Under Florida Law, it is a first degree misdeme anor, punishable asprovided in s. } 775.082 \text { or s. } 775.08, \text { Florida Statutes, to knowingly } \\
\text { sign more than one petition for an issue. Section 104. } 185, \text { Florida Statutes] } \\
\text { - If all requested information on this form is not completed, the form will not be valid. }
\end{array}
$$

| Your name: |  |
| :--- | :--- |
| Your address:__ Please Print Name as it appears on your Voter Information Card |  |
| City: $\quad$ Zip: $\quad$ County: |  |

$$
\square \text { Please change my legal address on my voter registration record to the above residence address (check box, if applicable). }
$$

Voter Registration Number: __ or Date of Birth: $\qquad$
I am a registered voter of Florida and hereby petition the Secretary of State to place the following proposed amendment to the Florida Constitution on the ballot in the general election:

BALLOT TITLE: Voting Restoration Amendment
BALLOT SUMMARY: This amendment restores the voting rights of Floridians with felony convictions after they complete all terms of their sentence including parole or probation. The amendment would not apply to those convicted of murder or sexual offenses, who would continue to be permanently barred from voting unless the Governor and Cabinet vote to restore their voting rights on a case by case basis.

ARTICLE AND SECTION BEING CREATED OR AMENDED: Article VI, § 4. FULL TEXT OF THE PROPOSED CONSTITUTIONAL AMENDMENT:
Article VI, Section 4. Disqualifications.-
(a) No person convicted of a felony, or adjudicated in this or any other state to be mentally incompetent, shall be qualified to vote or hold office until restoration of civil rights or removal of disability. Except as provided in subsection (b) of this section, any disqualification from voting arising from a felony conviction shall terminate and voting rights shall be restored upon completion of all terms of sentence including parole or probation.
(b) No person convicted of murder or a felony sexual offense shall be qualified to vote until restoration of civil rights.
(bc)No person may appear on the ballot for re-election to any of the following offices
(1) Florida representative,
(2) Florida senator,
(3) Florida Lieutenant governor,
(4) any office of the Florida cabinet,
(5) U.S. Representative from Flonida, or
(6) U.S. Senator from Florida
if, by the end of the current term of office, the person will have served (or, but for resignation, would have served) in that office for eight consecutive years.
$\overline{\text { DATE OF SIGNATURE } \quad X \quad X \quad \text { SIGNATURE OF REGISTERED VOTER }}$

Initiative petition sponsored by Floridians for a Fair Democracy, Inc., 3000 Gulf-to-Bay Blvd., Suite 503, Clearwater, FL 33759
Ir paid petition circulator is used:
Circulator's name

| RETURN TO: |
| :--- |
| Floridians for a Fair Democracy, Inc. |
| 3000 Gulf-to-Bay Blvd., Suite 503 |
| Clearwater, FL 33759 |

Circulator's address Culf-to-Bay Blvd., Suit

## B. Data Quality

Most counties had no data quality issues at all-no voter registration numbers were missing, invalid, or duplicative, and no dates were missing or improbable.

Table A. 1 below shows the counties with at least one data quality issue. I dropped petitions with a missing or invalid voter registration number, both because the petitions themselves were likely invalid and because they cannot be merged with the voter file. I also dropped duplicate petitions; if one of the duplicate petitions had a valid date, I kept the earlier petition. Finally, none of the petitions collected in Orange County had a date because the county instead provided an extract of the voter file subset to the records of registered voters who signed the petition. But the lack of a date is not problematic because the date is not necessary for any further analysis. As a result, I kept those petitions with missing dates.

Table A.1: Petition Data Quality

|  | Voter ID |  |  | Date |  |  |
| ---: | :---: | :---: | :---: | :---: | :---: | :---: |
| County | Missing | Invalid | Duplicate |  | Overall | Same Date |
|  | Missing | Improbable |  |  |  |  |
| Hillsborough | 19 | 2 | 0 | 0 | 0 | 0 |
| Orange | 0 | 0 | 0 | 0 | 50,273 | 0 |
| Palm Beach | 0 | 0 | 6,033 | 368 | 21 | 55 |
| Sarasota | 0 | 0 | 0 | 0 | 0 | 1 |
| St. Johns | 3 | 0 | 0 | 0 | 0 | 0 |
| Sumter | 0 | 0 | 0 | 0 | 5 | 0 |
| Total | 22 | 2 | 6,033 | 368 | 50,299 | 56 |

## C. Data Validation

Table A. 2 validates the number of petitions collected by comparing the number I collected per county to the totals reported by each county to the Division of Elections. ${ }^{2}$ The first row shows that my dataset actually includes slightly more petitions than those reported to the state. This is likely because, after the amendment qualified, the Division of Elections ceased updating the online portal, though counties may have continued to process the petitions submitted by the campaign. ${ }^{3}$

[^0]Table A.2: Petition Collection Validation

| County | Number of Petitions |  | Difference |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Collected | Reported | Total | \% |
| Alachua | 23,197 | 23,197 | 0 | 0\% |
| Baker | 370 | 370 | 0 | 0\% |
| Bay | 7,097 | 6,692 | 405 | 6\% |
| Bradford | 818 | 776 | 42 | 5\% |
| Brevard | 19,831 | 18,655 | 1,176 | 6\% |
| Broward | 107,489 | 102,704 | 4,785 | 5\% |
| Calhoun | 145 | 145 | 0 | 0\% |
| Charlotte | 8,612 | 8,487 | 125 | 1\% |
| Citrus | 3,381 | 3,273 | 108 | 3\% |
| Clay | 4,796 | 4,603 | 193 | 4\% |
| Collier | 3,567 | 3,100 | 467 | 15\% |
| Columbia | 2,207 | 2,090 | 117 | 6\% |
| Desoto | 76 | 324 | -248 | -77\% |
| Dixie | 92 | 92 | 0 | 0\% |
| Duval | 47,335 | 44,468 | 2,867 | 6\% |
| Escambia | 10,325 | 8,822 | 1,503 | 17\% |
| Flagler | 8,246 | 8,178 | 68 | 1\% |
| Franklin | 378 | 360 | 18 | 5\% |
| Gadsden | 3,813 | 3,259 | 554 | 17\% |
| Gilchrist | 246 | 246 | 0 | 0\% |
| Glades | 48 | 48 | 0 | 0\% |
| Gulf | 303 | 303 | 0 | 0\% |
| Hamilton | 148 | 148 | 0 | 0\% |
| Hardee | 113 | 113 | 0 | 0\% |
| Hendry | 241 | 374 | -133 | -36\% |
| Hernando | 5,294 | 5,178 | 116 | 2\% |
| Highlands | 173 | 886 | -713 | -80\% |
| Hillsborough | 72,960 | 69,745 | 3,215 | 5\% |
| Holmes | 62 | 62 | 0 | 0\% |
| Indian River | 3,364 | 2,236 | 1,128 | 50\% |
| Jackson | 380 | 380 | 0 | 0\% |
| Jefferson | 655 | 576 | 79 | 14\% |
| Lafayette | 50 | 50 | 0 | 0\% |
| Lake | 9,169 | 8,167 | 1,002 | 12\% |
| Lee | 19,310 | 20,055 | -745 | -4\% |
| Leon | 27,596 | 24,316 | 3,280 | 13\% |
| Levy | 788 | 736 | 52 | 7\% |
| Liberty | 65 | 99 | -34 | -34\% |
| Madison | 773 | 629 | 144 | 23\% |
| Manatee | 7,370 | 6,833 | 537 | 8\% |
| Marion | 12,646 | 11,948 | 698 | 6\% |
| Martin | 3,728 | 3,365 | 363 | 11\% |
| Miami-Dade | 90,443 | 82,534 | 7,909 | 10\% |
| Monroe | 1,767 | 1,792 | -25 | -1\% |
| Nassau | 1,402 | 1,296 | 106 | 8\% |
| Okaloosa | 1,617 | 1,261 | 356 | 28\% |
| Okeechobee | 268 | 268 | 0 | 0\% |
| Orange | 50,273 | 52,351 | -2,078 | -4\% |
| Osceola | 19,995 | 19,845 | 150 | 1\% |
| Palm Beach | 62,755 | 55,804 | 6,951 | 12\% |
| Pasco | 26,607 | 26,308 | 299 | 1\% |
| Pinellas | 69,223 | 67,910 | 1,313 | $2 \%$ |
| Polk | 29,062 | 27,617 | 1,445 | 5\% |
| Putnam | 3,080 | 3,031 | 49 | $2 \%$ |
| Santa Rosa | 1,837 | 1,642 | 195 | 12\% |
| Sarasota | 15,427 | 15,427 | 0 | 0\% |
| Seminole | 26,530 | 26,996 | -466 | -2\% |
| St. Johns | 8,182 | 7,773 | 409 | 5\% |
| St. Lucie | 16,879 | 15,761 | 1,118 | 7\% |
| Sumter | 2,564 | 2,265 | 299 | 13\% |
| Suwannee | 531 | 389 | 142 | 37\% |
| Taylor | 216 | 216 | 0 | 0\% |
| Union | 270 | 270 | 0 | 0\% |
| Volusia | 33,405 | 34,382 | -977 | -3\% |
| Wakulla | 1,017 | 1,017 | 0 | 0\% |
| Walton | 367 | 329 | 38 | 12\% |
| Washington | 287 | 224 | 63 | 28\% |
| Total | 881,261 | 842,796 | 38,465 | 5\% |

## D. Matching Petitions with Voter Registrations

I matched each petition to the statewide voter file by county ${ }^{4}$ and voter registration number in order to learn more about who signed each petition, including their party affiliation and race. Because the petition drive lasted multiple years, I used multiple copies of the statewide voter file from 2013, 2015, 2017, and 2018.

Table A. 3 shows that I matched more than 99 percent of petitions to a voter registration record. In general, when a petition matched to a registration record in multiple copies of the voter file over time, I took the registration in the most recent voter file.

[^1]Table A.3: Identifying Registration of Petitioners

| County | Year of Voter File Match |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | 2018 | 2017 | 2015 | 2013 | None |
| Alachua | 22,161 | 914 | 46 | 0 | 76 |
| Baker | 355 | 14 | 0 | 0 | 1 |
| Bay | 6,908 | 164 | 8 | 1 | 16 |
| Bradford | 794 | 20 | 1 | 0 | 3 |
| Brevard | 19,149 | 594 | 51 | 1 | 36 |
| Broward | 103,543 | 3,341 | 328 | 9 | 268 |
| Calhoun | 140 | 5 | 0 | 0 | 0 |
| Charlotte | 8,307 | 267 | 5 | 0 | 33 |
| Citrus | 3,236 | 121 | 8 | 0 | 16 |
| Clay | 4,467 | 271 | 15 | 2 | 41 |
| Collier | 3,355 | 175 | 29 | 0 | 8 |
| Columbia | 2,141 | 57 | 3 | 0 | 6 |
| Desoto | 73 | 3 | 0 | 0 | 0 |
| Dixie | 83 | 9 | 0 | 0 | 0 |
| Duval | 46,057 | 1,088 | 89 | 4 | 97 |
| Escambia | 9,976 | 265 | 60 | 2 | 22 |
| Flagler | 7,976 | 223 | 7 | 2 | 38 |
| Franklin | 369 | 9 | 0 | 0 | 0 |
| Gadsden | 3,666 | 127 | 14 | 0 | 6 |
| Gilchrist | 229 | 16 | 0 | 0 | 1 |
| Glades | 44 | 3 | 0 | 0 | 1 |
| Gulf | 292 | 8 | 2 | 0 | 1 |
| Hamilton | 143 | 5 | 0 | 0 | 0 |
| Hardee | 108 | 4 | 0 | 0 | 1 |
| Hendry | 229 | 9 | 2 | 0 | 1 |
| Hernando | 5,029 | 231 | 8 | 1 | 25 |
| Highlands | 157 | 10 | 6 | 0 | 0 |
| Hillsborough | 70,208 | 2,323 | 149 | 10 | 270 |
| Holmes | 60 | 2 | 0 | 0 | 0 |
| Indian River | 3,162 | 146 | 39 | 0 | 17 |
| Jackson | 368 | 11 | 0 | 0 | 1 |
| Jefferson | 624 | 25 | 3 | 0 | 3 |
| Lafayette | 50 | 0 | 0 | 0 | 0 |
| Lake | 8,705 | 359 | 45 | 4 | 56 |
| Lee | 18,634 | 600 | 19 | 2 | 55 |
| Leon | 25,916 | 1,403 | 217 | 4 | 56 |
| Levy | 762 | 22 | 3 | 0 | 1 |
| Liberty | 62 | 3 | 0 | 0 | 0 |
| Madison | 753 | 15 | 5 | 0 | 0 |
| Manatee | 6,964 | 336 | 32 | 0 | 38 |
| Marion | 12,214 | 363 | 25 | 0 | 44 |
| Martin | 3,488 | 198 | 29 | 0 | 13 |
| Miami-Dade | 87,141 | 2,659 | 379 | 21 | 243 |
| Monroe | 1,651 | 105 | 0 | 0 | 11 |
| Nassau | 1,329 | 60 | 4 | 0 | 9 |
| Okaloosa | 1,508 | 94 | 10 | 0 | 5 |
| Okeechobee | 254 | 12 | 1 | 0 | 1 |
| Orange | 50,230 | 37 | 0 | 0 | 6 |
| Osceola | 19,154 | 701 | 13 | 3 | 124 |
| Palm Beach | 62,487 | 50 | 12 | 3 | 203 |
| Pasco | 25,532 | 910 | 24 | 9 | 132 |
| Pinellas | 66,727 | 2,170 | 83 | 6 | 237 |
| Polk | 27,954 | 911 | 58 | 0 | 139 |
| Putnam | 2,979 | 83 | 4 | 0 | 14 |
| Santa Rosa | 1,732 | 80 | 17 | 1 | 7 |
| Sarasota | 15,358 | 22 | 0 | 0 | 47 |
| Seminole | 25,122 | 1,137 | 108 | 8 | 155 |
| St. Johns | 7,743 | 371 | 19 | 0 | 49 |
| St. Lucie | 16,312 | 452 | 52 | 1 | 62 |
| Sumter | 2,441 | 98 | 12 | 0 | 13 |
| Suwannee | 512 | 15 | 3 | 0 | 1 |
| Taylor | 211 | 5 | 0 | 0 | 0 |
| Union | 255 | 14 | 0 | 0 | 1 |
| Volusia | 32,338 | 884 | 50 | 13 | 120 |
| Wakulla | 966 | 45 | 4 | 0 | 2 |
| Walton | 334 | 23 | 2 | 1 | 7 |
| Washington | 275 | 11 | 1 | 0 | 0 |
| Total | $\begin{gathered} \hline 851,502 \\ (96.58 \%) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 24,708 \\ (2.75 \%) \\ \hline \end{gathered}$ | $\begin{gathered} 2,104 \\ (0.22 \%) \\ \hline \end{gathered}$ | $\begin{gathered} 108 \\ (0.0 \%) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 2,839 \\ (0.33 \%) \\ \hline \end{gathered}$ |

## E. Constructing Precinct-Level Demographics

## 1. Using Statewide Voter File

I used an October 2018 copy of the statewide voter registration file, the latest copy from before the November 2018 election, to compute precinct-level racial and age demographics using registrants' listed race and date of birth. I appended turnout in the November 2018 election to the voter registration list using a January 2019 copy of the statewide voter history file, the first copy published since the November 2018 election.

For each precinct, I calculated the percentage of registrants and voters who were Black as well as the percentage of registrants and voters who were aged eighteen to thirty-four, forty-five to sixty-four, and sixty-five and over as of March 12, 2019.

## 2. Using American Community Survey

I used the 2017 five-year estimates of the American Community Survey (ACS) to compute additional precinct-level racial and class demographics based on the number of Black residents and mean household income per Census block group.

In general, the ACS does not report data at the precinct level. The ACS instead provides aggregate demographic measures at the Census block level. A Census block is a parallel administrative unit of a similar size; each Census block is part of a larger Census tract within a particular county. I transformed the data from the Census block level to the precinct level based on the block-group and precinct of the 91 percent of registrations that were geo-coded with the highest accuracy score of 1 and the highest accuracy type of "rooftop."

## F. Supplemental Petition Results

Figure A. 2 depicts the cumulative number of valid petitions collected by the campaign per month. It reveals that there were essentially two different petition drives for Amendment 4, with little progress for three years followed by a sudden surge beginning in the summer of 2017.

Figure A.2: Cumulative Petitions by Month


## III.

## Ballots

## A. Data Collection

I made a public information request to the supervisor of elections of each county for the ballots cast in the November 2018 election. I initially collected ballot-level data from fifty-eight counties and ultimately was able to use ballotlevel data from fifty-two counties.

In general, the availability and quality of ballot-level data depended on the vendor each county used to run its elections. In DeSoto, Franklin, Glades, Jefferson, Lee, Miami-Dade, and Palm Beach counties, the supervisors of election were not able to generate the necessary data for varying reasons. For example, both Glades and Jefferson use election software called AccuVote, which could not output ballot-level data, while Miami-Dade and Palm Beach only had ballots available for manual inspection. Further, Hardee never responded to my public information request; Calhoun did respond, but after my analysis was complete.

The exact ballot data provided, like the availability of ballot data generally, depended on the vendor the county used for vote tabulation. Of the counties where I initially collected data, Baker, Hernando, Liberty, and St. Lucie counties provided literal ballot images, which I did not process, while Columbia County provided ballot data with unfamiliar formatting. Further, counties that used Dominion as their vendor rather than Election Systems \& Software (ES\&S) could not provide the precinct in which each ballot was cast, while counties that
used ES\&S could not link the first and second pages of a ballot with the third and fourth pages.

Table A. 4 reports the number of votes for Amendment 4 in the ballot-level data by county, including whether I could link a vote for Amendment 4 to a vote for statewide office (e.g., governor). In general, I could observe both Amendment 4 and a statewide race for about five million ballots. However, Broward county had ES\&S software and used a particularly long ballot, within which the gubernatorial election was on the first page and Amendment 4 was on the third or fourth page. As a result, while I collected and processed ballot-level data from Broward County, I was unable to link voters' choices for Amendment 4 to voters' choices for statewide office.

Table A.4: Ballot Data Available for Amendment 4 Votes

| County | Precinct Available? | Votes Recorded For Amendment 4 |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | Observe Governor? |  | \% Same Ballot-Page |
|  |  | Yes | No |  |
| Alachua | No | 84,321 | 0 | 100.0\% |
| Bay | Yes | 63,888 | 0 | 100.0\% |
| Bradford | Yes | 10,594 | 0 | 100.0\% |
| Brevard | Yes | 284,252 | 0 | 100.0\% |
| Broward | Yes | 0 | 712,745 | 0.0\% |
| Charlotte | Yes | 88,909 | 0 | 100.0\% |
| Citrus | Yes | 71,492 | 0 | 100.0\% |
| Clay | Yes | 73,778 | 0 | 100.0\% |
| Collier | Yes | 78,431 | 0 | 100.0\% |
| Dixie | Yes | 5,856 | 0 | 100.0\% |
| Duval | Yes | 346,596 | 0 | 100.0\% |
| Escambia | Yes | 130,405 | 0 | 100.0\% |
| Flagler | Yes | 53,311 | 0 | 100.0\% |
| Gadsden | Yes | 20,158 | 0 | 100.0\% |
| Gilchrist | No | 7,421 | 0 | 100.0\% |
| Gulf | Yes | 5,942 | 0 | 100.0\% |
| Hamilton | Yes | 4,590 | 0 | 100.0\% |
| Hendry | Yes | 8,964 | 0 | 100.0\% |
| Highlands | Yes | 40,172 | 0 | 100.0\% |
| Hillsborough | Yes | 523,943 | 0 | 100.0\% |
| Holmes | Yes | 6,839 | 0 | 100.0\% |
| Indian River | Yes | 74,999 | 0 | 100.0\% |
| Jackson | Yes | 16,109 | 0 | 100.0\% |
| Lafayette | Yes | 2,830 | 0 | 100.0\% |
| Lake | Yes | 156,348 | 0 | 100.0\% |
| Leon | No | 141,111 | 0 | 100.0\% |
| Levy | No | 17,208 | 0 | 100.0\% |
| Madison | No | 6,477 | 0 | 100.0\% |
| Manatee | Yes | 164,885 | 0 | 100.0\% |
| Marion | Yes | 154,475 | 0 | 100.0\% |
| Martin | Yes | 78,584 | 0 | 100.0\% |
| Monroe | No | 23,486 | 0 | 100.0\% |
| Nassau | Yes | 43,761 | 0 | 100.0\% |
| Okaloosa | Yes | 84,602 | 0 | 100.0\% |
| Okeechobee | No | 11,360 | 0 | 100.0\% |
| Orange | Yes | 480,919 | 0 | 100.0\% |
| Osceola | Yes | 116,111 | 0 | 100.0\% |
| Pasco | Yes | 211,460 | 0 | 100.0\% |
| Pinellas | Yes | 437,865 | 0 | 100.0\% |
| Polk | Yes | 247,043 | 0 | 100.0\% |
| Putnam | No | 23,063 | 0 | 100.0\% |
| Santa Rosa | Yes | 55,654 | 0 | 100.0\% |
| Sarasota | Yes | 213,220 | 0 | 100.0\% |
| Seminole | Yes | 200,980 | 0 | 100.0\% |
| St. Johns | Yes | 131,589 | 0 | 100.0\% |
| Sumter | Yes | 74,975 | 0 | 100.0\% |
| Suwannee | Yes | 16,066 | 0 | 100.0\% |
| Taylor | Yes | 8,000 | 0 | 100.0\% |
| Union | Yes | 4,901 | 0 | 100.0\% |
| Volusia | Yes | 231,945 | 0 | 100.0\% |
| Wakulla | Yes | 14,309 | 0 | 100.0\% |
| Walton | Yes | 30,579 | 0 | 100.0\% |
| Washington | Yes | 9,129 | 0 | 100.0\% |
|  | No | 314,447 | 0 | 100.0\% |
| All Counties | Yes | 5,079,458 | 712,745 | 87.7\% |
|  | Overall | 5,393,905 | 712,745 | 88.3\% |

## B. Data Validation

Table A. 5 validates the data collected by comparing the total number of votes cast for governor in the ballot-level data with the total number of voters reported by the counties to the state. For counties where ballot coverage was poor, I hypothesized that counties did not provide mail ballots. To test this theory, I aggregated the number of registrants in these problematic counties who cast a ballot by mail in the November 2018 election, as reported in a January 2019 copy of the statewide voter file. The data largely confirms my hypothesis.

Table A.5: Ballot Validation by County

| County | Total Votes for Governor |  | Ballot Coverage |  | Votes by Mail |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Aggregate Results | Indiv. Ballots | Difference | Percent |  |
| Alachua | 116,175 | 84,321 | 31,854 | 72.6\% | (31,393) |
| Bay | 63,888 | 63,888 | 0 | 100.0\% |  |
| Bradford | 10,594 | 10,594 | 0 | 100.0\% |  |
| Brevard | 284,252 | 284,252 | 0 | 100.0\% |  |
| Broward | 715,519 | 714,324 | 1,195 | 99.8\% |  |
| Charlotte | 87,912 | 88,909 | -997 | 101.1\% |  |
| Citrus | 71,494 | 71,492 | 2 | 100.0\% |  |
| Clay | 94,068 | 73,778 | 20,290 | 78.4\% | $(20,192)$ |
| Collier | 156,988 | 97,552 | 59,436 | 62.1\% | $(59,475)$ |
| Dixie | 5,858 | 5,856 | 2 | 100.0\% |  |
| Duval | 381,875 | 346,596 | 35,279 | 90.8\% | $(64,433)$ |
| Escambia | 130,405 | 130,405 | 0 | 100.0\% |  |
| Flagler | 53,325 | 53,311 | 14 | 100.0\% |  |
| Gadsden | 20,144 | 20,158 | -14 | 100.1\% |  |
| Gilchrist | 7,421 | 7,421 | , | 100.0\% |  |
| Gulf | 5,950 | 5,942 | 8 | 99.9\% |  |
| Hamilton | 4,593 | 4,590 | 3 | 99.9\% |  |
| Hendry | 8,972 | 8,964 | 8 | 99.9\% |  |
| Highlands | 40,176 | 40,172 | 4 | 100.0\% |  |
| Hillsborough | 527,294 | 523,943 | 3,351 | 99.4\% |  |
| Holmes | 6,841 | 6,839 |  | 100.0\% |  |
| Indian River | 74,999 | 74,999 | 0 | 100.0\% |  |
| Jackson | 16,111 | 16,109 | 2 | 100.0\% |  |
| Lafayette | 2,853 | 2,830 | 23 | 99.2\% |  |
| Lake | 156,339 | 156,348 | -9 | 100.0\% |  |
| Leon | 141,111 | 141,111 |  | 100.0\% |  |
| Levy | 17,208 | 17,208 | , | 100.0\% |  |
| Madison | 7,676 | 6,477 | 1,199 | 84.4\% | $(1,179)$ |
| Manatee | 164,885 | 164,885 | 0 | 100.0\% |  |
| Marion | 156,307 | 154,475 | 1,832 | 98.8\% |  |
| Martin | 78,591 | 78,584 | 7 | 100.0\% |  |
| Monroe | 36,586 | 23,486 | 13,100 | 64.2\% | (13,041) |
| Nassau | 43,808 | 43,761 | 47 | 99.9\% |  |
| Okaloosa | 84,723 | 84,602 | 121 | 99.9\% |  |
| Okeechobee | 11,360 | 11,360 | 0 | 100.0\% |  |
| Orange | 479,351 | 480,919 | -1,568 | 100.3\% |  |
| Osceola | 116,111 | 116,111 | 0 | 100.0\% |  |
| Pasco | 213,431 | 211,471 | 1,960 | 99.1\% |  |
| Pinellas | 439,590 | 437,865 | 1,725 | 99.6\% |  |
| Polk | 247,295 | 247,043 | 252 | 99.9\% |  |
| Putnam | 28,303 | 23,063 | 5,240 | 81.5\% | $(5,811)$ |
| Santa Rosa | 76,207 | 55,654 | 20,553 | 73.0\% | $(15,009)$ |
| Sarasota | 213,220 | 213,220 | 0 | 100.0\% |  |
| Seminole | 201,025 | 200,980 | 45 | 100.0\% |  |
| St. Johns | 131,696 | 131,589 | 107 | 99.9\% |  |
| Sumter | 74,978 | 74,975 | 3 | 100.0\% |  |
| Suwannee | 16,033 | 16,066 | -33 | 100.2\% |  |
| Taylor | 8,000 | 8,000 | 0 | 100.0\% |  |
| Union | 4,903 | 4,901 | 2 | 100.0\% |  |
| Volusia | 231,004 | 231,945 | -941 | 100.4\% |  |
| Wakulla | 14,311 | 14,309 | 2 | 100.0\% |  |
| Walton | 30,579 | 30,579 | 0 | 100.0\% |  |
| Washington | 9,134 | 9,129 | 5 | 99.9\% |  |
| Total | 6,321,472 | 6,127,361 | 194,111 | 96.9\% |  |

## C. Improvement over Ecological Inference

Without ballot-level data, social scientists would need to make an ecological inference, using aggregate vote patterns at the precinct level to estimate how individuals may have voted. A simple version of this approach is visualized by Figure A.3, below, which plots the share of support for Amendment 4 against the share of support for the Republican candidate for governor. Each point is a particular precinct. The pattern suggests that about 35 percent, rather than about 40 percent, of individuals who voted for Republican Ron DeSantis for governor supported Amendment 4.

Figure A.3: Predicting Partisan Support for Amendment 4 with Ecological Inference


One reason that a simple ecological inference underestimates Republican support for Amendment 4 is that Republican voters behaved differently depending on the political context of their precinct. For example, Figure A. 4 below shows that Republican voters who lived in areas that were more Democratic were more supportive of Amendment 4 than those who lived in more Republican areas.

Figure A.4: Testing the Ecological Inference


## D. Supplemental Ballot Results

Table A. 6 calculates multiple measures of partisan support for Amendment 4, using either the contest for governor or the contest for senate to identify the partisanship of each voter. The main specification examines all ballots for which the vote for statewide contests and Amendment 4 were connected. However, it is possible that some votes for Amendment 4 were the result of people simply voting "Yes" or "No" on all amendments, without specifically considering Amendment 4. As a robustness check, the final two columns limit the ballots considered to those where the voter was more likely to be expressing a true preference on Amendment 4 . The first robustness check limits the ballots to those in which there were at least one yes and at least one no vote on the amendments; the second limits the ballots to those in which there were either at least one yes and at least one no vote on the amendments or at least one valid vote and one invalid vote. Regardless, partisan support for Amendment 4 was consistent across all specifications.

| Ballots | Reference | Amendment 4 Vote | Support for Amendment 4 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | All Amendment 4 Votes With Partisanship ( $\mathrm{N}=5,393,905$ ) | Limited to Amendment Attention Check |  |
|  |  |  |  | $\geq 1 \text { Yes } \& \geq 1 \text { No }$ | $\begin{aligned} & \geq 1 \text { Yes } \& \geq 1 \text { No OR } \\ & \geq 1 \text { Valid } \& \geq 1 \text { Invalid } \end{aligned}$ |
| D | Governor | Yes | 86.1\% | (N6.9\% | 86.0\% |
| R | Governor | Yes | 40.0\% | $35.2 \%$ | 35.7\% |
| D | Governor | No | 10.9\% | 12.4\% | 11.8\% |
| R | Governor | No | $56.4 \%$ | 63.8\% | 61.6\% |
| D | Senator | Yes | 85.1\% | 85.8\% | 85.0\% |
| R | Senator | Yes | 40.7\% | 35.9\% | $36.4 \%$ |
| D | Senator | No | 11.9\% | 13.5\% | 12.9\% |
| R | Senator | No | 55.6\% | 63.1\% | 60.9\% |

IV.

Correctional Records
The Florida Department of Corrections has made available individual-level information on all persons who have been released from state prison since October 1997. For each of the 386,627 observed releases, the data listed in relevant part the released individual's internal identification number, full name, race, gender, date of birth, sentence start and end dates, and adjudication details, including whether their adjudication was withheld and whether their incarceration was for a misdemeanor. As the Florida Bar has explained,

Florida judges have a special authority vested upon them to "withhold adjudication" in a criminal matter .... The statute provides the court with the ability to withhold adjudication after the imposition of a probation sentence without imposing upon the defendant a conviction and the collateral consequences that accompany a conviction. ${ }^{5}$
The Department has so far declined to make available analogous information on the individuals who have been released from state supervision, most often probation. ${ }^{6}$ However, the Department previously provided such a file in mid-2015 in response to a request from the Project on Accountable Justice (PAJ), which generously shared that data with me. For each of the 1,559,099 observed releases from supervision, the data listed the same information as in the prison release file described above, although the variable names could be different. However, the PAJ data did not cover the period from mid-2015 through 2018.

To address this, I used alternative data that the Department did make available. Every few months, the Department has posted a snapshot with similar individual-level information on persons who were on state supervision at the time of the report. I began to gather these snapshots in January 2013. There were a total of six snapshots from January 2013, January 2015, June 2015, April 2017, October 2018, and January 2019, some of which were generously provided by Cyrus O'Brien. The snapshots contained between 156,070 and 171,521 records each. Using these snapshots, I determined the subpopulation of individuals who appeared in at least one probation snapshot before January 2019 but did not appear in the January 2019 data because they were previously released.

I combined the different supervision data and took the latest record available for each person, as defined by the matching methodology discussed below. I then removed any person from my combined probation release data who also appeared in my prison release data, such that I could distinguish between
5. George E. Tragos \& Peter A. Sartes, Withhold of Adjudication: What Everyone Needs to Know, FlA. BAR J., Jan./Feb. 2008, at 48, https://www.floridabar.org/the-florida-bar-journal/withhold-of-adjudication-what-everyone-needs-to-know/ [https://perma.cc/KP5Y-WJQD].
6. See E-Mail from Kristine Dougherty, Operations and Mgmt. Consultant Manager, Bureau of Rsch. and Data Analysis, Florida Dep't of Corrections, to Michael Morse (June 4, 2019) (on file with author).
persons with felony convictions based on whether or not they were previously in prison.

Importantly, a substantial number of the people in my dataset that were released from supervision appeared to have never lost their voting rights. In total, about 760,000 persons had a status of adjudication withheld and about 73,000 were convicted of a misdemeanor. ${ }^{7}$ But there may be measurement error in this information simply because it is not central to the mission of the Department of Corrections to track the collateral consequences of a criminal conviction.

In total, I have about 1.8 million individual-level records of persons who may have been disenfranchised prior to Amendment 4. It is important to underscore that, by definition, this does not include any persons who were disenfranchised because of a felony in another state or for a violation of federal law. Beyond this, the number is reasonably in line with previous estimates of the size of the population. ${ }^{8}$

## V. <br> Clemency Records

The Office of Executive Clemency currently takes the position that "no release of any clemency record is permissible absent the express permission of the Governor." ${ }^{\prime \prime}$ The current governor has declined to provide the names and dates of birth of persons who were granted clemency during his term or the terms of prior governors. ${ }^{10}$ However, in 2011, I began to gather information on the population of persons who had been granted clemency, when the Office of Executive Clemency took a different legal position. ${ }^{11}$

The data I obtained listed each individual restored the right to vote through part of 2012, including their full name, race, gender, date of birth, and date and type of clemency. Although I am missing subsequent grants of clemency from
7. This is in line with the Sentencing Project's report on felon disenfranchisement in Florida, which notes that "as much as 40 percent of the total probation population holds this 'adjudication withheld' status." Christopher Uggen, Ryan Larson \& Sarah Shannon, Sent’g Project, 6 million Lost Voters: State-Level Estimates of Felony Disenfranchisement 5 n. 1 (2016), https://www.sentencingproject.org/wp-content/uploads/2016/10/6-Million-Lost-Voters.pdf [https://perma.cc/T2L3-5JN5].
8. See Sarah K.S. Shannon, Christopher Uggen, Jason Schnittker, Melissa Thompson, Sara Wakefield, \& Michael Massoglia, The Growth, Scope, and Spatial Distribution of People with Felony Records in the United States, 1948-2010, 54 Demography 1795 (2017) (estimating Florida had $1,818,825$ ex-felons in 2010, 307,655 of which were considered ex-prisoners and $1,511,170$ exprobationers).
9. E-mail from Rana Wallace, General Counsel, Fla. Comm'n on Offender Rev., Off. of Exec. Clemency, to Michael Morse (June 24, 2019) (on file with author).
10. See E-Mail from Rana Wallace, General Counsel, Fla. Comm'n on Offender Rev., Off. of Exec. Clemency, to Michael Morse (Oct. 31, 2018) (on file with author).
11. See E-Mail from Jane Tillman, Director, Commc'ns \& Legis. Affs., Fla. Parole Comm'n, to Michael Morse (Mar. 1, 2011) (on file with author).

2012 through 2018 , there were only about 3,000 such grants. ${ }^{12}$ In contrast, there are 374,370 clemency records in my dataset.

I used a subset of the data on persons who were automatically restored the right to vote by former Governor Charlie Crist to analyze the party registration of people with felony convictions. Table A. 7 shows there are 151,527 such records, of which I estimated that there are 150,510 unique individuals, using the matching methodology described below, consistent with official state reports. All records have a valid clemency date and a valid race.

Table A.7: Data Available for Crist Restorations

| Quantity | Number | Percent |
| ---: | :---: | :---: |
| Est. Overall Persons | 150,510 |  |
| Overall Records | 151,527 |  |
| Valid Date | 151,527 | $100.00 \%$ |
| Date During Crist | 151,527 | $100.00 \%$ |
| Valid Race | 151,527 | $100.00 \%$ |
| Black | 57,178 | $37.73 \%$ |
| White | 90,731 | $59.88 \%$ |
| Hispanic | 2,966 | $1.96 \%$ |
| Valid DOB | 151,524 | $99.99 \%$ |
| Valid First Name | 151,527 | $100.00 \%$ |
| Only First Initial | 163 | $0.11 \%$ |
| Valid Middle Initial | 93,034 | $61.40 \%$ |
| Valid Last Name | 151,527 | $100.00 \%$ |
| Only Last Initial | 0 | $0.00 \%$ |

I also used the full clemency data to determine whether any person in either the correctional data or the sentencing data, described below, had been granted clemency by matching the datasets together according to the matching process described below.
VI.

## Matching Methodology

Given two lists with first name, middle initial, last name, and date of birth, I identified which records in the first list had a corresponding match in the second based on the following sequential rules:

1. I initially removed any punctuation and standardized the case of names.
2. I exactly matched by first name, middle initial, last name, and date of birth. I considered two records with missing middle

[^2]initials to be an exact match.
3. I then exactly matched by first name, last name, and date of birth, and identified matched records where the middle initial was present in one record but not the other.
4. I next standardized the first names in both lists by transforming any nickname to its root name according to a third-party dataset called pdNickname compiled by Peacock Data. I only looked for nicknames that were identified as short-form or diminutive nicknames in pdNickname. I also only considered transformations of nicknames to root names with the highest relationship quality scores (less than five, on a scale of one to one hundred). It was possible for nicknames to map to multiple root names and for these multiple root names to be assigned the same quality score. In these cases, for each nickname, I took the most common root name among all Florida registered voters with the same gender. I then exactly matched by standardized first name, middle initial, last name, and date of birth.
5. I exactly matched by standardized first name, last name, and date of birth, and identified matched records where the middle initial was present in one record but not the other.
6. I next exactly matched by middle initial, last name, date of birth, and gender, and identified matched records where the string distance between the first names was less than or equal to two using the optimal string alignment method implemented in the stringdist R package.
7. I finally exactly matched by standardized first name, middle initial, and date of birth, and identified matched records where the string distance between last names was less than or equal to 1.

I estimated the number of false matches produced by the above method using a permutation-based test. ${ }^{13}$ If two distinct people shared the same full name and date of birth, the matching methodology would produce a false match. To get a sense of the rate of such false matches, I permuted the date of birth in the first list of records by 35 days and repeated the matching process. Because 35 days is divisible by 7 , the permuted birthdate would fall on the same day of week as the original birthdate. By definition, any match using a permuted record was a false match. The difference between the number of matches using the true and permuted records thus provided an estimate of the number of true matches. To be clear, I both added and subtracted 35 days to show a symmetry in the expected number of false matches, but the original number of matches is an upper bound.

[^3]VII.

Supplemental Registration and Turnout Results
Table A. 8 breaks down the preferred estimate of initial Amendment 4 registrants based on the six steps of the matching methodology described above.

Table A.8: Match Quality for Amendment 4 Registrants

| Population of Persons with Felony Convictions | Specification | Exact <br> Match | Middle Initial Not Inconsistent | Account for Nicknames | Both <br> (2) and (3) | Account in First | for Typos in Last |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | (1) | (2) | (3) | (4) | (5) | (6) |
| Previously in Prison | Baseline | 5,522 | 1,292 | 25 | 13 | 164 | 105 |
|  | +35 days | 0 | 2 | 0 | 0 | 0 | 0 |
|  | -35 days | 2 | 2 | 1 | 0 | 0 | 0 |
| Not Previously in Prison | Baseline | 3,371 | 1,890 | 15 | 15 | 130 | 99 |
|  | +35 days | 0 | 7 | 0 | 1 | 1 | 0 |
|  | -35 days | 1 | 4 | 0 | 0 | 1 | 0 |

Table A. 9 does the same for those registrants who were automatically restored the right to vote by former Governor Crist.

Table A.9: Match Quality for Crist Registrants

| Specification | Exact <br> Match | Middle Initial <br> Not Inconsistent | Account for Nicknames | Both(2) and (3) | Account for Typos |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  | in First | in Last |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Baseline | 19,507 | 9,074 | 157 | 126 | 923 | 557 |
| +35 days | 32 | 108 | 2 | 18 | 34 | 11 |
| -35 days | 26 | 123 | 2 | 21 | 21 | 12 |

Figure A. 5 shows the number of people who registered to vote as a result of Amendment 4 by day. The yellow points represent the best estimate of which registrations were Amendment 4 registrations. These people were previously in the custody of the Department of Corrections, and there is no indication that their adjudication was withheld, that their conviction was for a misdemeanor, or that they were subsequently granted a still-valid clemency. Because these variables may have been measured with error, and because some people with felony convictions whose eligibility does not legally stem from Amendment 4 might nonetheless believe it does, the gray points represent all possible Amendment 4 registrations. The gray points will always be above (greater than) the yellow points. Under either specification, the most common day for Amendment 4 registration was the first day the amendment went into effect.

Figure A.5: Initial Amendment 4 Registrations by Day


Table A. 10 details the source of the different estimates of Amendment 4 registrations visualized in Figure A.5. The first panel focuses on those persons released from state prison. The second focuses on those released from state supervision, which is almost always probation. In each panel, Table A. 10 presents the baseline specification first, followed by the results of the permutation-based test to estimate the number of false positive registrations. Overall, there are very few false positives.

Table A.10: Multiple Estimates of Initial Amendment 4 Registrations

| Population of Persons <br> with Felony Convictions |  | Best Estimate | May Have Arleady Had Voting Rights |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Specification | Amendment 4 <br> Registrations | Received <br> Clemency | Convicted of <br> Misdemeanor | Adjudication <br> Withheld |
|  | Baseline | 7,121 | 449 | 0 | 2 |
|  | -35 days | 5 | 1 | 0 | 0 |
|  | +35 days | 2 | 2 | 0 | 0 |
| Not Previously in Prison | Baseline | 5,520 | 993 | 399 | 4,987 |
|  | -35 days | 6 | 4 | 0 | 7 |
|  | +35 days | 9 | 4 | 3 | 20 |

The columns separate out the best estimate of Amendment 4 registrations from the number of additional registrations by persons who may have already had the right to vote. It is important to consider the best estimate in the context of the additional estimates because there may be measurement error in who has been convicted of a misdemeanor, has had their adjudication withheld, or has subsequently received clemency. The significant number of persons who had a status of adjudication withheld complicates efforts to isolate the impact of

Amendment 4 on voter registration. These people had likely never lost their voting rights but did not realize as much until Amendment 4.

Table A. 11 reports the party of registration of initial Amendment 4 registrations with a permutation test to show that there were very few false matches.

Table A.11: Party of Registration of Initial Amendment 4 Registrants

| Population | Number of Releases Likely Disenfranchised Before Amendment 4 | Specification | Registration between January-June 2019 |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Overall | \% | Dem | Rep | NPA |  |  |
|  |  |  |  |  |  |  | As Is | Likely D | Likely R |
| All Restorations | 807,367 | Baseline | 12,638 | 1.6\% | 6,275 | 3,044 | 2,955 | 1,722 | 1,233 |
|  |  | Permute +35 days | 11 | 0.0\% | 5 | 3 | 3 | 0 | 1 |
|  |  | Permute - 35 days | 11 | 0.0\% | 6 | 4 | 1 | 0 | 0 |
| African-Americans | 266,786 | Baseline | 5,912 | 2.2\% | 4,567 | 199 | 1,033 | 989 | 44 |
|  |  | Permute +35 days | 4 | 0.0\% | 4 | 0 | 0 | 0 | 0 |
|  |  | Permute - 35 days | 7 | 0.0\% | 4 | 3 | 0 | 0 | 0 |
| Others | 540,581 | Baseline | 6,726 | 1.2\% | 1,708 | 2,845 | 1,922 | 734 | 1,188 |
|  |  | Permute +35 days | 7 | 0.0\% | 1 | 3 | 3 | 0 | 1 |
|  |  | Permute - 35 days | 4 | 0.0\% | 2 | 1 | 1 | 0 | 0 |

Table A. 12 does the same for registration and turnout by party for Crist registrants.

Table A.12: Party of Registration and Turnout of Crist Registrants

| Population | Restorations | Specification | Registration |  |  |  |  |  |  | Turnout |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Overall | \% | Dem | Rep | NPA |  |  | Overall | \% | Dem | Rep | NPA |
| All Restorations | 150,510 | Baseline | 30,344 | 20.2\% | 16,643 | 6,544 | 6,955 | 4,219 | 2,736 | 16,097 | 10.7\% | 9,406 | 3,928 | 2,682 |
|  |  | Permute +35 days | 205 | 0.1\% | 82 | 70 | 52 | 21 | 21 | 137 | 0.1\% | 53 | 51 | 32 |
|  |  | Permute - 35 days | 205 | 0.1\% | 79 | 70 | 54 | 28 | 16 | 145 | 0.1\% | 57 | 50 | 38 |
| African-Americans | 56,670 | Baseline | 13,957 | 24.6\% | 11,488 | 425 | 2,012 | 1,939 | 73 | 7,423 | 13.1\% | 6,576 | 173 | 663 |
|  |  | Permute +35 days | 98 | 0.2\% | 47 | 27 | 23 | 10 | 6 | 62 | 0.1\% | 29 | 19 | 13 |
|  |  | Permute - 35 days | 92 | 0.2\% | 38 | 32 | 21 | 13 | 6 | 67 | 0.1\% | 30 | 24 | 13 |
| Others | 93,840 | Baseline | 16,387 | 17.5\% | 5,155 | 6,119 | 4,943 | 2,280 | 2,663 | 8,674 | 9.2\% | 2,830 | 3,755 | 2,019 |
|  |  | Permute +35 days | 107 | 0.1\% | 35 | 43 | 29 | 11 | 15 | 75 | 0.1\% | 24 | 32 | 19 |
|  |  | Permute - 35 days | 113 | 0.1\% | 41 | 38 | 33 | 15 | 10 | 78 | 0.1\% | 27 | 26 | 25 |

VIII.

Fines and Fees

## A. Data Collection

The Florida Court Clerks and Comptrollers maintain the Comprehensive Case Information System (CCIS), which is "a secured single point of search for statewide court case information."14 The CCIS has a voluminous amount of information about felony cases in the state, such as the defendant's full name, race, gender, and date of birth, and each charge and sentence, including whether it was a misdemeanor and whether adjudication was withheld.

In general, the CCIS is organized by uniform case numbers (UCN). Each UCN includes a defendant-specific identifier, such that the unit of analysis is the defendant-case. I thus treated a single case with multiple defendants as if it were multiple cases. I used my matching method described above to link individual defendants across cases and counties. After dropping a small number of cases with inconsistent reporting, my final dataset includes roughly four hundred thousand cases and two hundred and forty thousand persons.

[^4]The CCIS mandates that county clerks report the total amount of fines and fees assessed in each case, the current balance owed, and the date of last payment. In addition to what is reported in CCIS, individuals may also be assessed additional fees, such as for the cost of collection, supervision, or room and board. ${ }^{15}$

The CCIS data is not well-suited for assessing the amount of restitution an individual is required to pay. Although CCIS permits county clerks to provide similar information about restitution, it is only mandatory if the data is already available in the local case management system. The information, though, is often not tracked because restitution is typically owed to a third-party and is not collected by the court system. ${ }^{16}$ As a result, I did not report data about restitution in the main text.

## B. Data Validation

The Florida Court Clerks and Comptrollers compiles an annual report on the assessment and payback of fines and fees that offers an approximate benchmark for validating the CCIS data. ${ }^{17}$ The report tracks the fiscal year of October 1 through September 30. ${ }^{18}$ It includes the "Amount Actually Assessed" in each county, which is defined as "fines, court costs and other monetary penalties and fees, service charges and costs actually imposed by the court at the time of sentencing or re-sentencing, or other type of disposition of the case., ${ }^{19}$ Because the 2018 report was generated using CCIS, the data provided should match the annual report. Comparing the two then should serve as a validation that I have used the data correctly. However, the report did not detail whether it generated the population of cases based on, for example, the filing date or disposition date. Assuming it was the disposition date, it did not say when the report itself was generated, which would matter to the extent that counties do not immediately provide their case data or subsequently update a case to include additional fines and fees. Further, Alachua, Columbia, Dixie, Indian River, and

[^5]Union counties did not report any information for the sub-category of "discretionary fines," so the annual report is incomplete.

Table A. 13 compares the total amount assessed for all cases in my dataset with a disposition date between October 1, 2017 and September 30, 2018, to the amount reported as "Amount Actually Assessed" in the statewide report. The percentage difference is also reported. In general, the data I collected roughly resembles the data in the statewide report.

Table A.13: Validation of Fines and Fees Data

| County | Total Assessment |  | \% Difference |
| :---: | :---: | :---: | :---: |
|  | Dataset | Annual Report |  |
| Alachua | \$3,522,335 | \$3,000,758 | 17\% |
| Baker | \$402,433 | \$344,825 | 17\% |
| Calhoun | \$353,786 | \$320,401 | 10\% |
| Charlotte | \$3,488,285 | \$3,361,665 | 4\% |
| Columbia | \$2,091,964 | \$1,684,985 | 24\% |
| Dixie | \$96,608 | \$141,733 | -32\% |
| Flagler | \$698,953 | \$654,690 | 7\% |
| Franklin | \$156,134 | \$187,147 | -17\% |
| Gadsden | \$211,925 | \$320,128 | -34\% |
| Hendry | \$785,045 | \$772,807 | 2\% |
| Highlands | \$2,646,255 | \$2,216,700 | 19\% |
| Holmes | \$1,207,845 | \$1,237,747 | -2\% |
| Indian River | \$13,617,825 | \$1,917,160 | 610\% |
| Jefferson | \$67,959 | \$71,000 | -4\% |
| Levy | \$215,979 | \$330,066 | -35\% |
| Liberty | \$84,266 | \$88,630 | -5\% |
| Madison | \$365,130 | \$461,211 | -21\% |
| Monroe | \$1,071,499 | \$1,138,521 | -6\% |
| Nassau | \$1,387,548 | \$581,730 | 139\% |
| Okaloosa | \$2,585,729 | \$3,376,854 | -23\% |
| Orange | \$16,334,358 | \$15,701,284 | 4\% |
| Putnam | \$1,120,097 | \$1,045,923 | 7\% |
| Santa Rosa | \$2,312,610 | \$2,413,718 | -4\% |
| Sumter | \$1,913,249 | \$1,891,327 | 1\% |
| Taylor | \$516,901 | \$513,258 | 1\% |
| Union | \$262,430 | \$209,808 | 25\% |
| Volusia | \$6,752,311 | \$4,906,996 | 38\% |
| Total | \$64,269,459 | \$48,891,072 | 31\% |

## C. Supplemental Results

I merged the CCIS sentencing data to a June 2019 copy of the statewide voter file based on the matching methodology described above to identify the distribution of fines and fees for initial Amendment 4 registrants.

Table A. 14 shows the high quality of each match to the voter file.

Table A.14: Sentencing Data to Voter File Match Quality

| Exact |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Specification | Middle Initial <br> Match <br> Not Inconsistent | Account for <br> Nicknames <br> $(2)$ | Both <br> (2) <br> and (3) <br> $(4)$ | Account for Typos <br>  <br> in First <br> $(5)$ | in Last <br> $(6)$ |  |
| Baseline | 2,010 | 218 | 7 | 0 | 58 | 22 |
| +35 days | 0 | 0 | 0 | 0 | 0 | 0 |
| -35 days | 0 | 1 | 1 | 0 | 1 | 0 |

Part III.A reports the preferred specification of the distribution of fines and fees per initial Amendment 4 registrants. Table A. 15 shows that the distribution of fines and fees is similar when using an alternative measure of initial Amendment 4 registrants.

Table A.15: Fines and Fees by Person Initially Registered (Robust)

|  | \# Initial <br> Registrations <br> (27 of 67 counties) | Percentile |  |  |  |  |  | Registrants with Balances |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Amount Due |  |  | Balance Remaining |  |  |  |
|  |  | 25th | 50th | 75th | 25th | 50th | 75th |  |
| All Registrants | 2,963 | \$698 | \$1,250 | \$2,340 | \$0 | \$671 | \$1,564 | 73\% |
| Black Registrants | 1,336 | \$714 | \$1,318 | \$2,351 | \$151 | \$809 | \$1,781 | 80\% |
| White Registrants | 1,578 | \$687 | \$1,198 | \$2,312 | \$0 | \$563 | \$1,409 | 67\% |


[^0]:    2. That data is available at Voting Restoration Amendment Valid Petition Signatures, Fla. DEP'T OF STATE, DIV. OF ELECTIONS, https://dos.elections.myflorida.com/initiatives/initdetail.asp?account=64388\&seqnum=1 [https://perma.cc/X94W-H2AL].
    3. See, e.g., E-mail from Ray Bolden, Candidate and VBM Coordinator, Okaloosa County Supervisor of Elections, to Michael Morse (Feb. 25, 2019) (on file with author) (explaining the discrepancy between petitions collected and petitions reported online by noting that counties cannot "post results directly to the state site. . . . Instead we have to mail letters to the Division of Elections and they post the results").
[^1]:    4. I match by county because valid petitions "must . . . be submitted to the Supervisor of Elections's office in the county of residence of the signee in accordance with Rule 1S-2.0091, Florida Administrative Code." Fla. Dep’t of State, Div. of Elections, 2018 Initiative Petition HANDBOOK 2 (2018), https://fldoswebumbracoprod.blob.core.windows.net/media/697659/initiative-petition-handbook-2018-election-cycle-eng.pdf [https://perma.cc/QY7H-A9KV].
[^2]:    12. See Hand v. Scott, 285 F. Supp. 3d 1289, 1310 (N.D. Fla. 2018), vacated and remanded sub nom. Hand v. DeSantis, 946 F.3d 1272 (11th Cir. 2020) ("Since 2011, a period of seven years, that figure has plummeted-less than 3,000 people have received restoration.").
[^3]:    13. See Marc Meredith \& Michael Morse, The Politics of the Restoration of Ex-Felon Voting Rights, 41 Q.J. PoL. SCI. 41, 58 (2015) (proposing the technique).
[^4]:    14. See COMPREHENSIVE CASE INFO. SYS., https://www.flccis.com/ocrs/login.xhtml [https://perma.cc/3WMQ-H6YK].
[^5]:    15. See Rebekah Diller, Brennan Ctr. for Just., The Hidden Costs of Florida's Criminal Justice System 27-33 (2010), https://www.brennancenter.org/sites/default/files/2019-08/Report_The\%20Hidden-Costs-Florida\%27s-Criminal-Justice-Fees.pdf [https://perma.cc/CH8DM85X] (listing LFOs established by Florida law, some of which were assessed post-trial).
    16. See, e.g., Lawrence Mower, Amendment 4 Will Likely Cost Millions to Carry Out. Here's Why., TAMPA BAY TIMES (Apr. 4, 2019), https://www.tampabay.com/florida-politics/2019/04/04/amendment-4-will-likely-cost-millions-to-carry-out-heres-why/ [https://perma.cc/ZH7T-6L62].
    17. See, e.g., Fla. Ct. Clerks \& Comptrollers, 2018 Annual Assessments and COLLECTIONS REPORT (2018), https://flccoc.org/wp-content/uploads/2018/12/2018-Annual-Assessments-and-Collections-Report.pdf [https://perma.cc/F5DX-L4JK]; see also Fla. Stat. Ann. $\S 28.246$ (statutory requirement).
    18. See FLA. Stat. AnN. § 166.241.
    19. Fla. Сt. CLERKS \& COMPTROLLERS, 2018 AnNUAL ASSESSMENTS AND COLLECTIONS REPORT, supra note 17, at 4.
