# Evaluating the Impact of Employing Local Tax Collectors to Improve State-Level Licensing Program Outcomes in Florida

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Article

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# Evaluating the Impact of Employing Local Tax Collectors to Improve State-Level Licensing Program Outcomes in Florida

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## Abstract

The improvement of public services is an important public policy objective, and several approaches have been proposed and implemented across all levels of government to achieve this goal. A recent policy in Florida (FL) fosters collaboration between local and state governments by allowing local tax collector (TC) offices to receive and support applications for the state's concealed weapons (CW) license program. We use 80,020 application

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records to estimate process improvements brought about by this policy. Our analysis shows that by using TCs, the time for the application to be processed was one third the time it needed via mail and about 3% at the regional office. The likelihood of errors in applications and supporting documents decreased significantly. The policy, therefore, has improved the effectiveness of the CW licensing service in FL. Similar initiatives can be adopted by government entities facing bottlenecks in permitting or licensing processes.

**Keywords**
collaboration, licensing, service improvement, concealed weapons

Concealed weapon (CW) licenses allow private citizens to carry firearms and other weapons in a concealed manner while in public places. Private citizens in the United States (US) may obtain such licenses in all states. However, laws differ across states as to whether citizens are entitled to obtain a concealed carry permit or not. In states with "shall issue" laws such as Florida (FL), responsible government agencies must issue CW licenses to all applicants who meet eligibility criteria, which usually include a clean background check and no history of mental illness. In most cases, carrying a CW without a license is a crime, albeit openly carrying firearms and other weapons is legal in some states (Cramer & Kopel, 1995).

Adopted in 1987, section 790.06 of FL's statutes requires the FL Department of Agriculture and Consumer Services (FDACS) to operate FL's CW license program and award licenses to qualified applicants. To qualify for a license, legal residents and US citizens must be at least 21 years of age, not suffer from infirmities that would prevent the safe handling of a firearm, not be a convicted felon, not be involved in controlled substance-related crimes in the previous 3 years, not be a habitual user of alcohol or other impairing substances, and demonstrate proficiency with a firearm.

FL's CW license program has seen tremendous growth since its inception in 1987 (Figure 1). During the first 12 years of FL's CW license program, the number of active licenses grew from 32,844 in 1988 to 235,532 in 1999, or an annual average growth of 16,893 licenses per year. In the subsequent 16 years, the number of active licenses has grown from 247,704 in 2000 to 1,598,213 in 2016, or an average annual growth of 79,441 licenses per year. Since 2012, the number of active licenses has grown by 645,798 or an annual growth of 129,159 licenses per year. This exponential growth in the number of active licenses can also be seen in the

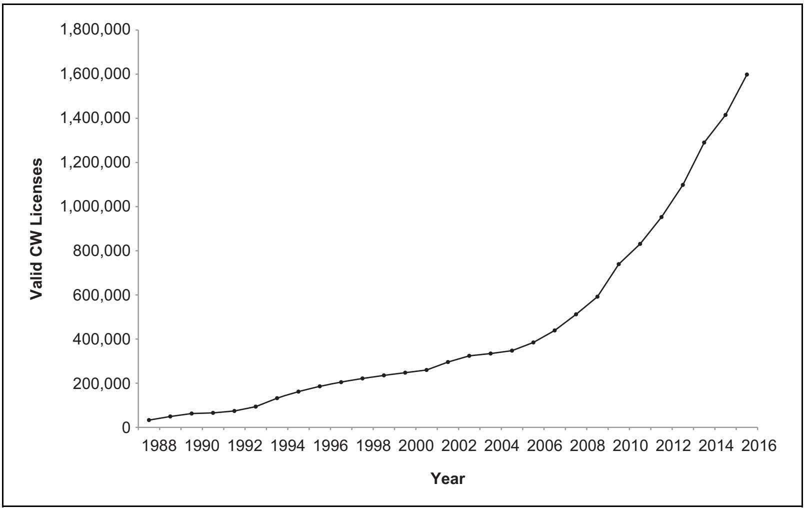


**Figure 1.** Number of active concealed weapons licenses issued by the state of Florida between 1988 and 2016.

number of new CW license applications received by the state of FL, which has grown from 33,449 in 2004 to 244,726 in 2016 (Figure 2). Resources at the state level, in terms of Full-Time Equivalent (FTE) positions in the division that administers CW licenses, have changed over time. A review of FL's General Appropriations Act shows that there has been steady, yet slow growth in personnel dedicated to this program. However, the growth in FTEs closely tracks the growth in the number of new CW applications.[1] Notably, FL has CW license reciprocity agreements with 36 states, implying that individuals licensed to carry CW in FL can also concealed carry in most other states.

Prior to 2014, individuals seeking an FL CW license needed to complete a firearms proficiency course and then apply in person at an FDACS Division of Licensing Regional Office or complete an application that would be mailed to the Division of Licensing's headquarters in Tallahassee, FL (Figure 3, panels A and B). While in-person applicants could complete the fingerprint requirement (background check) at the regional office, those applying by mail would have to visit their local Sheriff's office to complete the fingerprint requirement. Hence, mail applicants would complete a CW license application independently and send the application and supporting documents to the Division of Licensing's headquarters. In

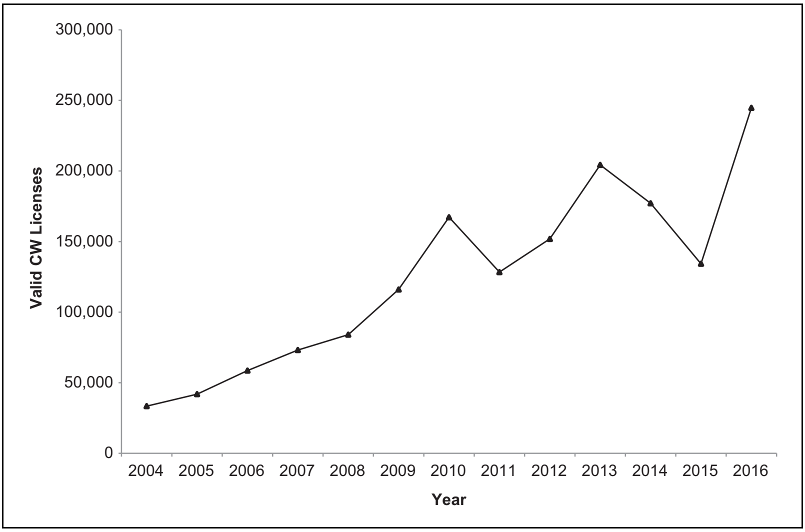


**Figure 2.** Number of new concealed weapons license applications received by the state of Florida between 2004 and 2016.

contrast, those applying in person at the regional offices could complete their applications on-site with the support of FDACS staff. The cost for a newly issued CW license is currently US$60, but applicants must also pay a fingerprint processing fee of US$42, for an initial license cost of US$102. Applicants seeking a renewal must pay US$50 if they live in-state and US$92 if they are out-of-state residents.

In 2014, the FL Legislature approved a revision of the 790.06 statute that allowed elected county tax collectors (TC) to enter an agreement with FDACS to receive CW applications at their local offices. TC offices that opt into the agreement are provided with specialized equipment and training to offer in-person support and verification of applications for completeness as well as the necessary equipment to complete a fingerprint report. Thus, the process that applicants experience at their local TC offices is no different from what they would experience if they visited the FDACS Division of Licensing regional office (Figure 3, panel C). The objectives of this policy were to address the exponential growth in the number of applications received by the program and expedite the CW license service. It is important to note that applications received at the TC offices are sent electronically to the Division's headquarters and are processed by FDACS Division staff.

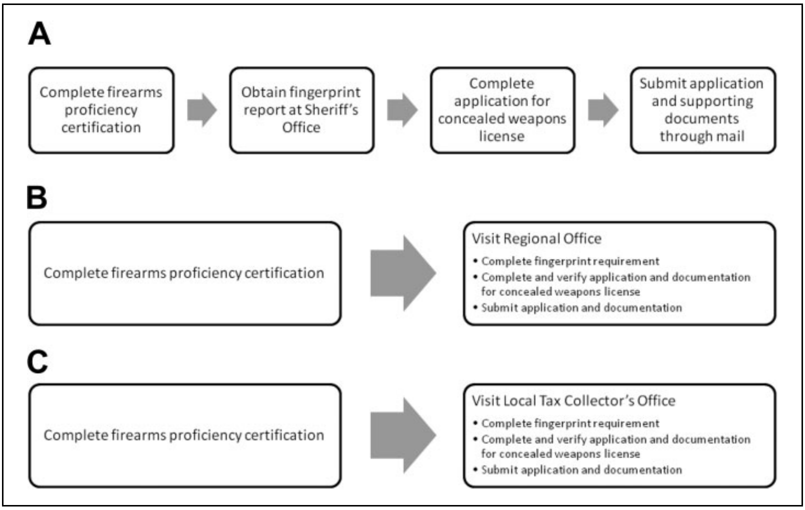


**Figure 3.** Three ways to apply for a Florida (FL) concealed weapons license. (A) Mail applicants must obtain a firearms proficiency certification, obtain a fingerprint report from local law enforcement, complete the application, and mail all documents with little or no support by FL Department of Agriculture and Consumer Services personnel. (B) Applicants who use a regional office must obtain a firearms proficiency certification before visiting the regional office, but all other requirements can be completed in person and with the support of regional office staff. (C) Applicants who use their local tax collector's office must obtain a firearms proficiency certification before visiting the tax collector's office, but all other requirements can be completed in person and with the support of regional office staff.

Hence, TCs serve as an intermediary helping citizens to complete, verify, and submit their CW applications. TC's offices levy a convenience fee of up to US$22 to CW license applicants who use their services, and all equipment necessary for the process such as the fingerprint capture machine are provided by FDACS at no cost to the TC office. Hence, TC offices bear no cost other than the staff time dedicated to assist applicants. It is also important to note that TCs are not compelled to participate in the program, instead their participation is voluntary, and they must initiate the agreement process. First-time applicants using the TC service pay US$124 (17.8% surcharge), in-state renewal applicants pay US$72 (30.5% surcharge), and out-of-state renewal applicants pay US$114 (19.3% surcharge).

The present study assesses changes in the effectiveness of FL's concealed firearms license issuance program brought about by the new policy implemented in 2014. In essence, the policy creates new physical points of contact for applicants to a state-awarded license while utilizing the public capacity at the local (county) level. The analysis focuses on two important measures related to the effectiveness of the license issuance service: (1) the time taken to process the application and (2) the number of applications containing errors or omissions in the application or supporting documents. We consider implementation of the policy as an intervention and evaluate differences in outcomes between the pre- and postimplementation groups.

Our approach employs a conceptual representation where we model license processing time frames as a zero-inflated negative binomial process. In addition, we employ propensity score matching to evaluate the difference in processing time for the pre- and postprogram implementation periods, changes in application errors and omissions for the pre- and postimplementation groups. Our analysis shows the policy intervention resulted in a notable reduction in processing time frames and proportion of errors in concealed firearm license applications. Our results show that this collaborative policy reduced the length of the application process by two thirds of the time needed postimplementation of the program versus applications submitted via mail, and about 3% of the time needed when applications were submitted at the regional office. Similarly, the likelihood that applications contained errors was reduced by 9% for omitted information in applications and 4% for supporting materials that did not meet quality standards.

To our knowledge, this is the first empirical study documenting and measuring effectiveness gains in government service delivery resulting from collaboration between state and local government entities. This study also evaluates an ongoing policy and provides a sense of how state and local governments, which operate at different scales, can collaborate to drastically improve service delivery. The rest of this article is organized as follows. Improving Delivery of Public Services section discusses public service delivery, including conceptual and empirical issues surrounding measuring improvements in delivery of these services. Data section describes the data, and Methods section outlines the analytical framework and the estimation strategy. Results are presented and discussed in Results section. This article ends with some concluding remarks.

## Improving Delivery of Public Services

The improvement of public services has been identified as an important public policy objective, and several approaches have been proposed and implemented across all levels of government to achieve this goal. In many cases, these approaches have mimicked performance improvement strategies that have proven successful in the private sector such as total quality management, six sigma, benchmarking, business process reengineering, process mapping, strategic planning, performance-based budgeting, or cost accounting (Hendrick, 2003; Siha & Saad, 2008). However, the complexity of services offered by the public sector makes the implementation of many of these strategies in governmental organizations problematic. As Ostrom (1973) explains, due to the nature of the services provided by public agencies, it is much more difficult to conceptualize and measure their success using traditional measurements of physical output.

Collaboration between government entities, or between government entities and nonprofit organizations, has also been proposed as strategy to improve delivery of public services. For instance, direct relations between the federal government and state or local governments are common in areas such as homeland security, law enforcement, disaster response, and economic development, among others (Davidson, 2007). Similarly, local governments may form intergovernmental agreements to collaborate in the provision of services requiring boundary-spanning infrastructure (LeRoux & Carr, 2007). Collaboration between state and local governments is also common, particularly when it involves sharing information to facilitate law enforcement and criminal justice activities (Pardo, Gil-Garcia, & Burke, 2008). Several studies have examined factors that facilitate or hinder such collaboration (e.g., Amirkhanyan, 2009; Davidson, 2007; Gazley, 2010; LeRoux & Carr, 2007; Pardo et al., 2008; Snavely & Desai, 2001).

Studies evaluating how government agencies function generally use operational or government capacity as a measure of performance. Capacity[2] is associated with the amount of professional and budgetary resources governments allocate to their agencies to carry out their operations and provide services effectively and efficiently (Deller, Nelson, & Walzer, 1992; Loh, 2015). Effectiveness measures the extent to which operations, programs, and services meet the needs of the community (Deller et al., 1992; Epstein, 1984). Minimizing the cost of these operations, programs, and services is what renders local governments efficient (Deller et al., 1992; Epstein, 1984).

## Data

The data used in this study consist of individual CW license application records from the 11 counties in FL whose TCs had entered agreements to receive applications at their local offices before April 2016. The data

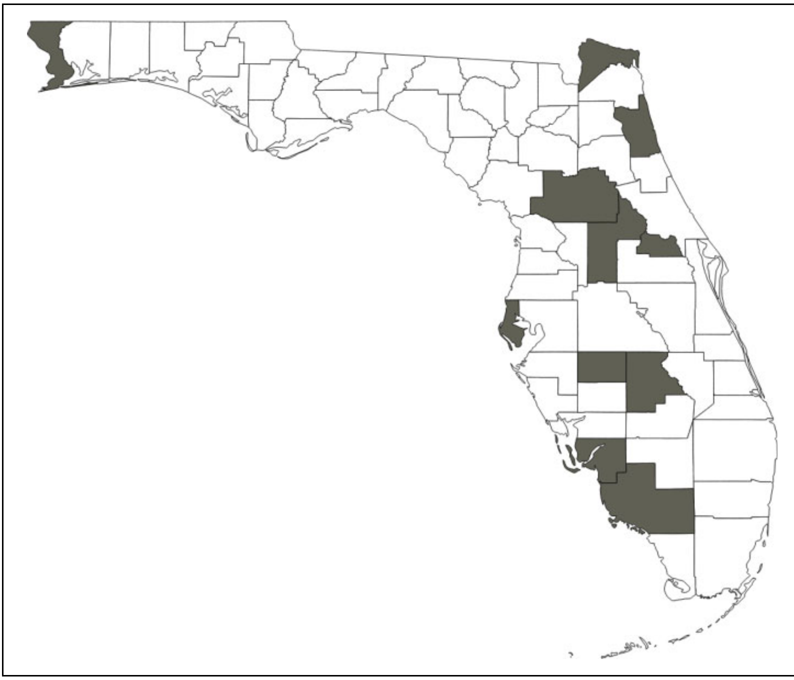

**Figure 4.** Map of participating counties.

include all CW license applications from these 11 counties issued between September 1, 2013, 1 full year before the first TC agreement was implemented, and April 12, 2016, the most recent period available at the time we initiated this study (Figure 4).[3] The data contain only new applications.

For each individual application record, the data include several important attributes of the applicant and the application process. Information about the applicant includes gender, race, and age, whether the applicant is an active duty member of the military or a military veteran, and the county in which the applicant lives in. The information about the process includes the date in which the application was received, the date in which the application was approved or denied, the number of days elapsed between these two dates, the application method (mail, FDACS' regional office, or TC), and indicators for whether the application contained errors of omission or a rejected fingerprint report. Errors of omission occur when the application contains information in the incorrect fields or when important fields are missing information. Rejected fingerprint reports occur when law enforcement agencies are unable to use the fingerprint report submitted with the application due to low quality, improper placement of the fingers, or similar issues.

The data set contains a total of 80,020 individual application records. Using the date in which the application was received and the known dates in which the TC program started in each county, we created a binary indicator (PROGRAM) that takes a unit value if the county was participating in the TC program at the time the application was received, and zero otherwise. Thus, our sample is divided into a preimplementation group (PROGRAM = 0) and a postimplementation group (PROGRAM = 1). Of all the CW license applications in our data set, 45% were processed after the TC program went into effect in the respective county, while the remaining 55% were processed prior to the program being available.

Table 1 provides information on the variables we examine for the whole sample. Specifically, the average age of applicants is 50 years, over 68% of the applicants in the sample are male and 90% are White. About 8.4% of applicants are active duty members of the military or have identified themselves as military veterans. Table 2 shows descriptive statistics for the pre- and postimplementation periods. A two sample *t* test with unequal variances is used to check for differences in the two periods in terms of demographic characteristics of applicants, workload, county of application, receiving location, and outcomes of interest. There are no statistically significant differences in demographic characteristics between the two periods, and we observe a slight increase in the number of military veterans after the TC program was implemented. The values reported by county do not report average volume of applications, but they do represent the percentage of applications in each county by program group. Each county instituted the program at a different date, so these results cannot be interpreted as growth rates.

Before implementation of the program, 49.7% of the applications were received at the FDACS regional offices and 50.3% were received by mail. After implementation of the program, 51%, 28%, and 21% of the applications were received by the TC's offices, FDACS regional offices, and mail, respectively. There is large variation in the amount of time it takes to process a CW license, ranging from a single day to an observed maximum of 2,604 days in our sample (i.e., a single observation from Hardee county).[4] The bottom panel of Table 2 presents information for the three outcomes of interest: length of the application process (DAYS), proportion of applications with rejected fingerprint reports (FINGERP), and proportion of applications with errors of omission (OMISSION). In terms of the length of the

**Table 1.** Descriptive Statistics.

| Variable | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| Demographics (Di) | | | | |
| Age | 50.0554 | 16.3286 | 18 | 99 |
| Female | 0.3158 | — | 0 | 1 |
| Asian | 0.0135 | — | 0 | 1 |
| Black | 0.0568 | — | 0 | 1 |
| Native | 0.0034 | — | 0 | 1 |
| Unknown | 0.0218 | — | 0 | 1 |
| White | 0.9045 | — | 0 | 1 |
| Military | 0.0841 | — | 0 | 1 |
| Intervention (Ii) | | | | |
| Program | 0.4498 | — | 0 | 1 |
| Receiving location (Li) | | | | |
| Taxcol | 0.2298 | — | 0 | 1 |
| Mail | 0.3704 | — | 0 | 1 |
| Regional | 0.3998 | — | 0 | 1 |
| Workload (Wi) | | | | |
| Applications | 193.3688 | 46.8667 | 134.291 | 244.726 |
| County (Ci) | | | | |
| Collier | 0.0714 | — | 0 | 1 |
| Escambia | 0.0901 | — | 0 | 1 |
| Hardee | 0.0067 | — | 0 | 1 |
| Highlands | 0.0364 | — | 0 | 1 |
| Lake | 0.1078 | — | 0 | 1 |
| Lee | 0.1912 | — | 0 | 1 |
| Marion | 0.0944 | — | 0 | 1 |
| Nassau | 0.0343 | — | 0 | 1 |
| Pinellas | 0.2106 | — | 0 | 1 |
| Seminole | 0.0883 | — | 0 | 1 |
| St. Johns | 0.0688 | — | 0 | 1 |
| Outcomes | | | | |
| Length of process (Ti) | | | | |
| Days | 15.5906 | 45.2095 | 1 | 2,604 |
| Errors (Hi) | | | | |
| Fingerp | 0.0614 | — | 0 | 1 |
| Omission | 0.1297 | — | 0 | 1 |

application process, the preimplementation group has a mean of 22 days, while the postimplementation group has a mean of 8 days. The *t* test rejects the null hypothesis that the two groups have equal means with more than 99% confidence. In addition, the mean difference between groups is

**Table 2.** Comparison of Means for the Pre- and Postimplementation Periods.

| | Preimplementation | | Postimplementation | | | | |
|---|---|---|---|---|---|---|---|
| Variables | Mean | Standard Deviation | Mean | Standard Deviation | Mean Difference | *t*-Statistica | DF |
| Demographics (Di) | | | | | | | |
| Age | 50.439 | 16.454 | 49.587 | 16.162 | 0.852 | 7.36 | 77,402.3 |
| Male | 0.683 | 0.465 | 0.686 | 0.464 | −0.003 | −0.00 | 76,969.2 |
| Asian | 0.014 | 0.118 | 0.013 | 0.112 | 0.001 | 1.54 | 78,129.8 |
| Black | 0.064 | 0.245 | 0.048 | 0.214 | 0.016 | 9.67 | 79,642.4 |
| Native | 0.003 | 0.056 | 0.003 | 0.056 | −0.000 | −0.99 | 74,918.8 |
| Unknown | 0.028 | 0.166 | 0.014 | 0.116 | 0.014 | 14.679 | 78,249.9 |
| White | 0.890 | 0.312 | 0.922 | 0.269 | −0.032 | −15.21 | 79,813.9 |
| Military | 0.026 | 0.160 | 0.155 | 0.362 | −0.129 | −62.52 | 47,465.7 |
| Workload (Wi) | | | | | | | |
| Applications | 169.881 | 33.784 | 222.098 | 44.575 | −52.217 | −1.8e+02 | 65,863.6 |
| County (Ci) | | | | | | | |
| Collier | 0.103 | 0.303 | 0.033 | 0.180 | 0.070 | 39.99 | 73,389.6 |
| Escambia | 0.124 | 0.329 | 0.049 | 0.216 | 0.075 | 38.70 | 76,541.2 |
| Hardee | 0.006 | 0.077 | 0.007 | 0.086 | −0.001 | −2.62 | 72,900.7 |
| Highlands | 0.019 | 0.138 | 0.057 | 0.232 | −0.038 | −27.37 | 55,805.7 |
| Lake | 0.169 | 0.375 | 0.033 | 0.178 | 0.136 | 67.67 | 65,518.6 |
| Lee | 0.169 | 0.375 | 0.218 | 0.413 | −0.049 | −17.58 | 73,498.1 |
| Marion | 0.082 | 0.273 | 0.110 | 0.313 | −0.028 | −13.83 | 71,933.8 |
| Nassau | 0.019 | 0.137 | 0.053 | 0.224 | −0.034 | −25.11 | 56,956.7 |
| Pinellas | 0.143 | 0.350 | 0.293 | 0.455 | −0.150 | −51.38 | 66,510.5 |

(continued)

**Table 2.** (continued)

| | Preimplementation | | Postimplementation | | | | |
|---|---|---|---|---|---|---|---|
| Variables | Mean | Standard Deviation | Mean | Standard Deviation | Mean Difference | *t*-Statistica | DF |
| Seminole | 0.109 | 0.312 | 0.062 | 0.242 | 0.047 | 24.19 | 79,778.2 |
| St. Johns | 0.057 | 0.232 | 0.083 | 0.276 | −0.026 | −14.17 | 70,421.6 |
| Receiving location (Li) | | | | | | | |
| Taxcol | — | | 0.511 | 0.450 | −0.511 | | |
| Mail | 0.503 | 0.499 | 0.208 | 0.406 | 0.295 | 91.96 | 80,016.6 |
| Regional | 0.497 | 0.499 | 0.281 | 0.449 | 0.216 | 64.40 | 79,307.2 |
| Outcomes | | | | | | | |
| Length of process (Ti) | | | | | | | |
| Days | 22.06 | 56.49 | 7.68 | 22.96 | 14.38 | 48.70 | 60,586.6 |
| Errors (Hi) | | | | | | | |
| Fingerp | 0.09 | 0.28 | 0.03 | 0.18 | 0.06 | 32.46 | 75,617.4 |
| Omission | 0.18 | 0.39 | 0.07 | 0.25 | 0.11 | 50.86 | 76,197.7 |
| Sample size | 44,026 | | 35,994 | | | | |

*Note*. For each one of our variables of interest, we test for difference in means using a two-sample *t* test with unequal variances (Ho: $\mu 1 = \mu 2$). DF = Degrees of Freedom.

estimated at 14 days, implying that on average, the length of the application process decreased by 14 days after the program implementation. This change can be attributed to the TC intervention, which is what we examine in this study.

Improvements in terms of the likelihood of encountering errors in the applications or supporting documents are also noteworthy. Regarding fingerprint reports that were returned by law enforcement officials due to low quality or other issues, the preimplementation group had a fingerprint return rate of 9%, while the postimplementation group had a rate of 3%. The *t* test once again rejects the null hypothesis of equal means with more than 99% confidence, and we report a reduction in returned fingerprint reports of 6% after the implementation of the TC program. Regarding errors of omission in CW license applications, the preimplementation group had an error rate of 18%, while the postimplementation group had an error rate of 7%. Once again, the *t* test supports rejecting the null hypothesis of equal error rates across groups with more than 99% confidence, and we estimate an 11% reduction in errors of omission after implementation of the TC program.

While comparing the pre- and postimplementation groups shows striking improvements in the CW licensing process brought about after the introduction of the TC program, a similar comparison by the type of application method yields additional insights (Table 3). For instance, Table 3 shows that licensing outcomes improved with the implementation of the TC program across all application types. In other words, even individuals who did not submit their CW license applications through the TC's offices experienced improvements after the program was implemented.

In terms of days elapsed between application submission and disposition, mail submissions took an average 32 days prior to implementation of the program but only 15 days after implementation of the program. The *t* test supports rejection of the null hypothesis of equal means across groups with more than 99% confidence. Applications submitted through the regional offices also experienced an improvement in terms of average length of the process from 12 days before the implementation of the program to 6 days after its implementation. The comparisons suggest similar improvements in the rates of returned fingerprint reports and errors of omission. Possible explanations for these spillover effects will be discussed later in this article.

Although this partial statistical analysis shows that after the implementation of the TC program the effectiveness of the CW license application process improved, it fails to account for potential confounding effects and could offer a distorted view of the effectiveness gains observed. To offer a

**Table 3.** Comparison of Means by Type of Application for the Pre- and Postimplementation Periods.

| | | Preimplementation | | Postimplementation | | | | |
|---|---|---|---|---|---|---|---|---|
| Outcome | Type | Mean | Standard Deviation | Mean | Standard Deviation | Mean Difference | *t*-Statistics | DF |
| Days | Tax collector | — | — | 5.81 | 18.81 | — | — | — |
| | Regional office | 11.55 | 37.12 | 5.85 | 19.52 | 5.70 | 17.95 | 31,483.9 |
| | Mail | 32.44 | 69.04 | 14.73 | 32.95 | 17.71 | 29.52 | 26,512.7 |
| Fingerp | Tax collector | — | — | 0.03 | 0.16 | — | — | — |
| | Regional office | 0.07 | 0.25 | 0.04 | 0.19 | 0.03 | 13.13 | 26,026.8 |
| | Mail | 0.10 | 0.30 | 0.04 | 0.20 | 0.06 | 18.66 | 19,206.3 |
| Omission | Tax collector | — | — | 0.05 | 0.22 | — | — | — |
| | Regional office | 0.08 | 0.27 | 0.03 | 0.17 | 0.05 | 19.48 | 28,927.5 |
| | Mail | 0.28 | 0.45 | 0.16 | 0.36 | 0.12 | 24.11 | 15,824.3 |

*Note.* DF = Degrees of Freedom.

more rigorous analysis, we proceed with an econometric analysis in the following section.

## Method

The objective of this study is to assess changes in the effectiveness of FL's concealed firearms license issuance program brought about by collaboration between the state agency issuing the licenses and county TC's who receive applications directly. We use three measures of effectiveness in our analysis. Specifically, we are interested in changes in the number of days it takes to process CW license applications, the likelihood that an application contains errors of omission, and the likelihood the application is supported by an unsuitable fingerprint report.

### *Processing Time*

An individual applying for a CW license prior to the implementation of the TC program could either submit the application by mail or visit an FDACS Division of Licensing Regional Office. Applications received by mail must pass an initial quality control for proper fingerprint records and omitted fields in their application. Individuals applying at the regional office received assistance from employees, which decreased the likelihood of these types of error. After proper screening for these errors, applications were officially reviewed by employees at the Division of Licensing headquarters. With the implementation of the TC program, applications received at the TC offices were prescreened by TC office staff and were also subsequently sent to headquarters for official review.

Upon arrival for official review at the headquarters, applications are allocated to employees for review and processing. Generally, we can expect that each application has a different processing time which can be attributed to the method of submission (mail, TC, and regional office), the type of application, and the processing ability of each employee. We also expect the processing time to differ pre- and postimplementation of the TC program.

Considering our full data set, we observed that the majority of the applications, about 79%, are processed within a day, which we coded as DAYS $= 0$ (see Figure 5). When we look at the pre- and postimplementation periods, we observe that about 72% and 87% of the applications, respectively, are processed within a day (Table 4). We also notice a striking change in the number of applications that were submitted at the TC office and were handled within a day.

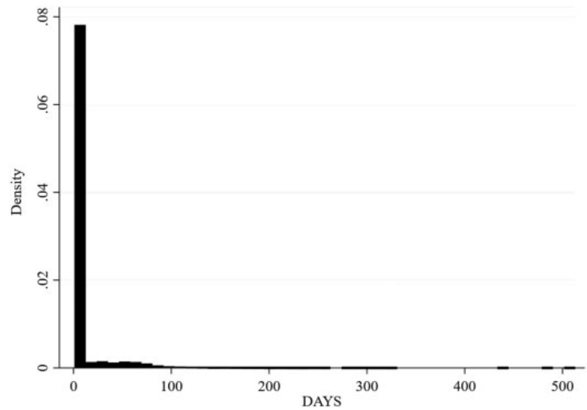


**Figure 5.** Length of the application process for full sample.

**Table 4.** Applications Processed Within 1 Day by Type of Application for the Full Sample and Pre- and Postimplementation Periods.

| Outcome | Type | Full Sample ($n$ = 80,020) Number (%) | Preimplementation ($n$ = 44,026) Number (%) | Postimplementation ($n$ = 35,994) Number (%) |
|---|---|---|---|---|
| Days = 0 | Tax collector | 16,432 (~20) | N/A (N/A) | 16,432 (~46) |
| | Regional office | 27,067 (~34) | 18,027 (~41) | 9,040 (~25) |
| | Mail | 19,380 (~25) | 13,553 (~31) | 5,827 (~16) |
| | Total | 62,879 (~79) | 31,580 (~72) | 31,299 (~87) |

## *Econometric Strategy*

While comparison of means across the pre- and postimplementation groups can identify measurable improvement in the CW licensing process, there are likely to be confounding variables (i.e., exogenous factors) affecting the number of days elapsed between the time an application is received and the time in which it is approved or denied as well as the number of errors of omission or rejected fingerprint reports. We can also expect some of these outcomes to mediate the impact of the TC program on other outcomes. For instance, we can expect the implementation of the TC program to result in a reduction in the number of days it takes to obtain a CW license as well as a reduction in the number of errors of omission. However, the reduction in the number of errors of omission is likely to result in a reduction in the number of days it takes to obtain a license. Hence, the error rate, which is an outcome of interest, impacts the length of the process, another outcome of interest.

## Linear Model

Initially, we estimate a linear equation relating the length of the CW license application process to all potential mediating factors, including the TC program as the intervention.

$$T_i = \alpha_0 + \alpha_1 D_i + \alpha_2 I_i + \alpha_3 L_i + \alpha_4 W_i + \alpha_5 H_i + \alpha_6 C_i. \tag{1}$$

$T_i$ represents the number of days elapsed between receipt and disposition of CW license application $i$, $D_i$ represents demographic characteristics of applicant $i$, $I_i$ is the indicator for the intervention (PROGRAM), $L_i$ is the indicator for the type of location that received the application, $W_i$ is the measure of the total workload of the licensing program, $H_i$ is the indicator of whether application $i$ contained an error or had its fingerprint report rejected, and $C_i$ is the county-specific indicator.

## Zero-Inflated Negative Binomial Model

To account for the count data nature of the application processing time variable and the existence of excess zeroes in the sample, we estimate a zero-inflated negative binomial model. Zero-inflated negative binomial distribution can also control for overdispersion in the distribution of the dependent variable (Cameron & Trivedi, 1986).

Parameters that may affect the time an application is processed, in this case within a day, include errors of omission or ineligible fingerprints, the place where the application was submitted, the method of application submission, and the workload of the processing center.[5] We model the count portion of the zero-inflated negative binomial model using the variables $L_i$, $W_i$, $H_i$, and $C_i$. We model the certain zeroes using the variable related to errors of omission and fingerprint results, $H_i$.

## Propensity Score Matching

Considering this as a pre–post study, we further explore the intervention of the TC program using a propensity score matching approach. Our sample includes information from the 11 counties that enacted the TC program. Each county enacted the program at a different time (refer to Note 4).

### *Errors of Omission and Fingerprint*

An additional issue with measuring the improvement in government processes brought about by the implementation of the TC program is the nature of the outcome variables used in the analysis. Namely, the event of encountering an error of omission or rejected fingerprint report can best be mapped using a binary indicator that takes a unit value when such an error exists and zero otherwise. As stated earlier, the TC program intervention can be expected to reduce not only the length of the CW license application process but also the number or proportion of applications containing errors of omission and whose fingerprint reports are rejected by law enforcement officials conducting required background checks. To find this impact, we estimate two Probit regression models, one for each of the potential application error variables ($H_i$), as follows:

$$Pr(Y = 1|\, x) = \Phi(x'\beta), \tag{2}$$

where $Pr$ denotes probability, $\Phi$ is the cumulative distribution function of the standard normal distribution, $x$ is the vector of independent variables ($D$, $I$, $L$, $W$, and $C$), and $\beta$ is the vector of unknown parameters. Estimates for unknown parameters were obtained using maximum likelihood estimation.

## Results

This section presents the estimation results for several models that can be used to explore the effect of the implementation of the TC program on the outcomes of interest. All models use the same sample of 80,020 described in the Data section. Table 5 presents the linear regression estimates. We consider this as a benchmark, and we note that there is a statistically significant decrease in the number of days of about 4 days after the TC program is implemented. We cannot attribute this change strictly to the TC program, as people can still select to submit their applications via mail or at the regional offices. In addition, considering that our dependent variable is a count-data variable with a very skewed distribution (Figure 5), Ordinary Least Squares (OLS) may not be the best approach to estimate a model.

**Table 5.** Linear Regression Results.

| | Linear Regression | | |
|---|---|---|---|
| Days | Coefficient | Standard Error | *p* Value |
| Age | −0.003 | 0.008 | .713 |
| Military | −2.083*** | 0.381 | .000 |
| Omission | 63.300*** | 0.730 | .000 |
| Fingerp | 65.162*** | 0.976 | .000 |
| Program | −4.248*** | 0.346 | .000 |
| Female | −1.116*** | 0.253 | .000 |
| Asian | −1.418 | 0.878 | .106 |
| Black | 2.343*** | 0.661 | .000 |
| Native | −0.710 | 1.025 | .488 |
| Unknown | 3.232 | 1.331 | .015 |
| CWIS | −4.079*** | 0.324 | .000 |
| WBFT | −4.949*** | 0.326 | .000 |
| Collier | −1.558*** | 0.566 | .006 |
| Escambia | −1.074* | 0.610 | .078 |
| Hardee | 6.110 | 5.755 | .288 |
| Highlands | 0.108 | 0.672 | .872 |
| Lake | −2.674*** | 0.612 | .000 |
| Lee | −0.064 | 0.379 | .865 |
| Marion | −2.212*** | 0.525 | .000 |
| Nassau | 0.509 | 0.580 | .380 |
| Seminole | −1.531*** | 0.546 | .005 |
| St. Johns | −1.199*** | 0.420 | .004 |
| Applications | 0.023*** | 0.004 | .000 |
| Constant | 4.249*** | 0.760 | .000 |

*Note.* $R^2 = .3726$. CWIS = Concealed Weapons Intake System; WBFT = Web Based Fast Track application.
Significance levels of *p*-values: *.10. **.05. ***.01.

## *Zero-Inflated Negative Binomial*

Estimated coefficients from the zero-inflated negative binomial regression on the number of days elapsed between receipt and disposition of an application are presented in Table 6. As explained in the Method section, the zero-inflated negative binomial[6] generates two separate models; a count model, in this case a negative binomial model to model the count process and a logit model to model which of the processes the zero outcome is associated with. The logit model predicts the excess zeros.

**Table 6.** Zero-Inflated Negative Binomial Results.

| | Zero-Inflated Negative Binomial | |
|---|---|---|
| Days | Coefficient | Standard Error |
| Count | | |
| Program = 1 | −.370*** | .020 |
| Mail | .306*** | .025 |
| WBFT | .036 | .025 |
| Applications | .002*** | .000 |
| Omission | .337*** | .016 |
| Fingerp | .441*** | .016 |
| Collier | −.040 | .034 |
| Escambia | .001 | .033 |
| Hardee | .555*** | .084 |
| Highlands | .169*** | .042 |
| Lake | −.090*** | .031 |
| Lee | .073 | .029 |
| Marion | −.021 | .032 |
| Nassau | .134*** | .044 |
| Pinellas | .089*** | .029 |
| Seminole | −.035 | .033 |
| Logit | | |
| Omission | −8.986 | 0.259 |
| Fingerp | −31.274 | 24,300.91 |
| Nonzero observations | 17,141 | |
| Loglikelihood (count) | −100,718.66 | |
| Zero observations | 62,879 | |
| Loglikelihood (logit) | −99,632.604 | |

*Note.* WBFT = Web Based Fast Track application.
Significance levels of *p*-values: *.10. **.05. ***.01.

The predictors PROGRAM, MAIL, REGIONAL, APPLICATIONS, OMISSIONS, and FINGERP in the portion of the negative binomial predicting the number of days it needs for the applications to be processed are all significant at the 1% level. Particularly, TC implementation reduces the log(count) of processing days by −0.37. Submitting the application via mail or through a regional office increases the number of processing days relative to using the TC office. The effect of the volume of applications, the existence of errors of omission, and ineligible fingerprints is positive suggesting a longer application process. We also observe five counties (namely, Hardee, Highlands, Lake, Nassau, and Pinellas) to be significant predictors. For four of these counties as compared to St. Johns county

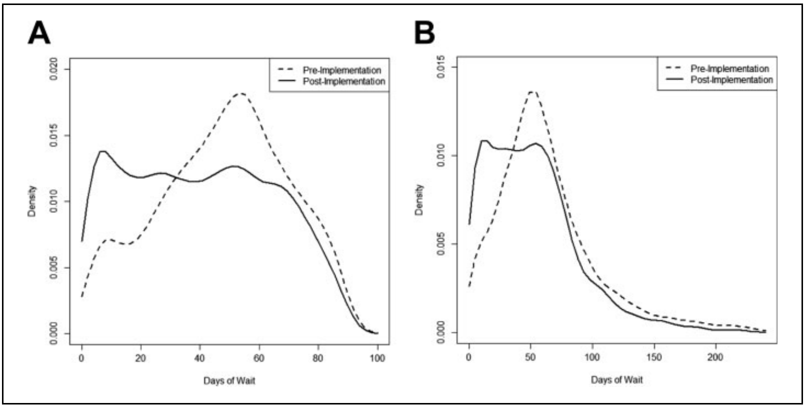


**Figure 6.** Density histograms for (A) the 90-day statutorily mandated period and (B) the 238-day period that includes 99% of all applications. Observations that were processed in the same day the application was received are omitted.

(baseline), the application processing period is longer, whereas for the Lake county, the application processing period is shorter.

Regarding the logit model, the predictor OMISSION predicts that excess zeros are also significant. The log odds of being an excessive zero would decrease by 8.99 for applications with an error of omission. The predictor FINGERP is not significant.

Our $\alpha$ coefficient is greater than zero ($\alpha = .584$), which justifies the zero-inflated negative binomial over the zero-inflated Poisson distribution. We also used the Vuong test to compare the zero-inflated model with an ordinary negative binomial regression model. A significant *z* test indicated that the use of the zero-inflated model is preferred.

We still need to consider that our results may be attributable to the large volume of applications that are processed in the pre- and postimplementation period within 1 day (72% and 86% for the pre- and postimplementation group, respectively). By law, the division of licensing has to inform applicants within 90 days of receipt of their application whether their license has been issued or denied. Examining our data, we observe a difference in the percentage of applications issued within the 90-day period (94% and 98% for the pre- and postimplementation group, respectively). Looking at the time frame when 99% of applications has been issued for the two groups, we see that for the preimplementation group 238 days elapsed, while 109 days elapsed for the postimplementation group. Figure 6 presents density histograms for the two groups for the 90-day statutorily mandated period

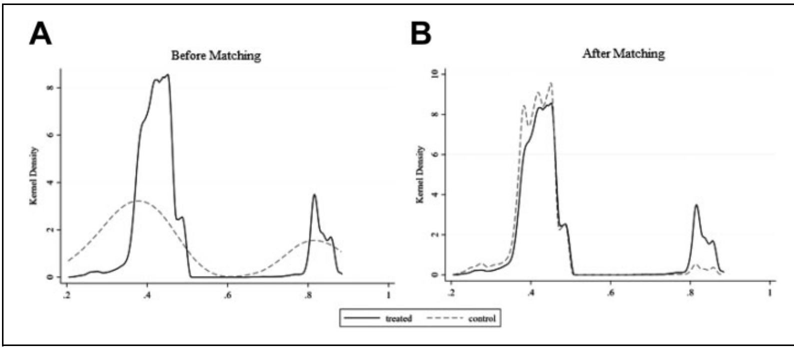


**Figure 7.** Propensity Score distribution before and after matching.

**Table 7.** Propensity Score Matching Results: Summary of Units On and Off Support

| Treatment Assignment | On Support | Total |
|---|---|---|
| Untreated | 44,026 | 44,026 |
| Treated | 35,994 | 35,994 |
| Total | 80,020 | 80,020 |

and the 238-day period that includes 99% of applications—excluding the 1-day cutoff for better visualization of the data. These graphs allude to the differences between the two periods. We also conduct a ratio test to evaluate statistical differences in the groups for the 90-day and the 238-day intervals. Both ratio tests verify the statistically significant difference in the days an application takes to be processed under the pre- and postimplementation scenarios with more than 99% confidence.

## *Propensity Score Matching*

To further examine how the TC intervention affected the processing time of CW applications, we used propensity score matching. We matched the pre- and postimplementation periods based on the applicant profile (Figure 7 and Table 7). The variables considered were age, gender, race, ethnicity, and military status. The applicant profile is considered independent of the outcome, in this case processing days.[7] If the applicant profile did not differ in the two periods, we can better see changes being attributed to the intervention. Our analysis suggests that the program reduces

**Table 8.** Propensity Score Matching Results: Estimated Treatment Effects Results.

| Variable | Sample | Treated | Controls | Difference | *SE* | *t*-Statistics |
|---|---|---|---|---|---|---|
| Processing days | Unmatched | 6.8119 | 21.339 | −14.527 | 0.319 | −45.55 |
| | ATT | 6.8119 | 36.116 | −29.304 | 5.636 | −5.20 |
| | ATU | 21.339 | 9.039 | −12.300 | | |
| | ATE | | | −19.949 | | |

*Note.* ATT = Average Treatment Effect on Treated; ATU = Average Treatment Effect on Untreated; ATE = Average Treatment Effect.

**Table 9.** Propensity Score Matching Results: Balancing Checking for Propensity Score Matching Estimator.

| | | Mean | | %Reduct | | *t* Test | |
|---|---|---|---|---|---|---|---|
| Variable | Sample | Treated | Control | %Bias | \|Bias\| | *t* | *p* > \|*t*\| |
| Age | Unmatched | 49.587 | 50.439 | −5.2 | | −7.35 | .000 |
| | Matched | 49.587 | 49.577 | 0.1 | 98.9 | 0.00 | .935 |
| Female | Unmatched | 0.314 | 0.317 | −0.7 | | −0.96 | .339 |
| | Matched | 0.314 | 0.311 | 0.6 | 9.4 | 0.83 | .408 |
| White | Unmatched | 0.921 | 0.890 | 10.7 | | 14.98 | .000 |
| | Matched | 0.921 | 0.924 | −0.7 | 93.2 | −1.06 | .289 |
| Black | Unmatched | 0.048 | 0.064 | −6.8 | | −9.54 | .000 |
| | Matched | 0.048 | 0.048 | 0.0 | 99.6 | 0.03 | .972 |
| Asian | Unmatched | 0.013 | 0.014 | −1.1 | | −1.53 | .125 |
| | Matched | 0.013 | 0.012 | 1.0 | 5.0 | 1.46 | .144 |
| Native | Unmatched | 0.004 | 0.003 | 0.7 | | 0.99 | .322 |
| | Matched | 0.004 | 0.002 | 1.2 | −76.6 | 1.70 | .089 |
| Military | Unmatched | 0.155 | 0.026 | 45.9 | | 66.89 | .000 |
| | Matched | 0.155 | 0.155 | 0.0 | 100.0 | 0.00 | 1.000 |

processing time by 26 days (Table 8). We also checked the balancing prior to accepting these results (Table 9).

## *Errors and Omissions*

We can expect that applications that contain errors of omission or are supported by rejected fingerprint reports experience drastically longer processing times. Both types of errors appear to have very similar effects on the length of the process and can be expected to result in lower processing times according to the zero-inflated negative binomial model (Table 6).

**Table 10.** Probit Regressions Results.

| | FINGERP | | | OMISSION | | |
|---|---|---|---|---|---|---|
| Variables | Coefficient | Standard Error | *dy/dx* | Coefficient | Standard Error | *dy/dx* |
| Age | 0.045*** | .001 | .004 | .006* | .000 | .001 |
| Military | 0.106*** | .039 | .010 | −.017 | .027 | −.003 |
| Program | −0.433*** | .027 | −.040 | −.518*** | .019 | −.096 |
| Female | 1.003*** | .018 | .093 | −.021 | .013 | −.004 |
| Asian | 0.243*** | .081 | .022 | .409*** | .047 | .076 |
| Black | −0.661*** | .071 | −.061 | .292*** | .024 | .054 |
| Native | −0.149 | .174 | −.014 | .093 | .108 | .017 |
| Unknown | 0.068 | .069 | .006 | .447*** | .034 | .083 |
| CWIS | −0.396*** | .033 | −.036 | −.658*** | .023 | −.122 |
| WBFT | −0.167*** | .020 | −.015 | −.844*** | .015 | −.157 |
| Collier | −0.036 | .035 | −.003 | −.296*** | .027 | −.055 |
| Escambia | −0.246*** | .039 | −.023 | −.227*** | .025 | −.042 |
| Hardee | −0.339*** | .124 | −.031 | −.176** | .077 | −.033 |
| Highlands | −0.195*** | .050 | −.018 | −.161*** | .036 | −.030 |
| Lake | −0.255*** | .033 | −.024 | −.245*** | .023 | −.046 |
| Lee | 0.001 | .027 | .000 | −.103*** | .020 | −.019 |
| Marion | −0.153*** | .034 | −.014 | −.054** | .023 | −.010 |
| Nassau | 0.256*** | .048 | .024 | .020 | .039 | .004 |
| Seminole | −0.070* | .037 | −.007 | −.170 | .025 | −.032 |
| St. Johns | −0.109*** | .040 | −.010 | −.078* | .029 | −.015 |
| Applications | 0.000 | .000 | .000 | .000*** | .000 | .000 |
| Constant | −4.247*** | 0.065 | | −0.910*** | 0.038 | |
| Adj./pseudo $R^2$ | | | 0.265 | | | 0.122 |
| *F*/LR $\chi^2$ | | | 9,796.450 | | | 7,543.380 |

*Note*. CWIS = Concealed Weapons Intake System; WBFT = Web Based Fast Track application.
Significance levels of *p*-values: *.10. **.05. ***.01.

The large impact of the two types of errors on the length of the application process highlights the importance of properly accounting for any impact that implementation of the TC program may have on the error rate. The left-side portion of Table 10 shows results for the Probit model that uses rejected fingerprint reports as the dependent variable. In terms of demographic characteristics of the applicants, this model shows that applicants who are older, female, Asian, and have active duty or military veteran status face a higher likelihood of receiving a fingerprint report that is later rejected by law enforcement officials. In contrast, Black applicants face a lower likelihood of receiving a fingerprint report that is rejected by law enforcement officials. Similarly, implementation of the TC program reduced the chances of obtaining a fingerprint report that was rejected by law enforcement for all applicants by 4%, according to the marginal effects estimate. Further, applications received at the regional offices and the TC's offices also had lower probability of being supported by a fingerprint report that was later rejected by law enforcement.

The right-side portion of Table 10 shows results for the Probit model that uses errors of omission as the dependent variable. This model shows that applications from older, Asian, Black, and unidentified race individuals have errors of omission more often than applications for other types of applicants. Implementation of the TC program also decreased the chances of applications containing errors of omission for all applicants by 9%, according to the marginal effects estimate. In addition, applications received at the regional offices and the TC's offices have lower likelihood of containing errors of omission than applications received by mail.

## Conclusion

The most striking finding of this study is that after implementation of the program, more than half of new applicants opt into using the TC offices as their application method. Besides providing a new and popular choice for applicants, the policy has a similarly striking impact on effectiveness outcomes and even seems to have a spillover positive impact on other application methods. This article provides alternative empirical approaches and estimation techniques to measure the impact of the TC program on the CW licensing process. All estimated models yield similar results, showing that the average length of the process and the likelihood of errors in applications and supporting documents have decreased after implementation of the program. Moreover, implementation of the program has benefited all applicants, who can now get their licenses, on average, at one third of the time it takes to submit the application via mail and also have a slight advantage in processing time versus submitting their application at the regional office.

The dynamic that errors of omission and defective fingerprint reports play in the licensing process is one of the most interesting aspects uncovered in the analysis. When a submitted application contains an error of omission or is supported by a bad fingerprint report, the Division of Licensing must contact the applicant by mail to inform them of the deficiency in the application, and the applicant must correct the problem by submitting additional materials by mail. It is therefore not surprising that applications that contain errors take, on average, more than 26 days longer to process than applications that do not. However, by increasing access to staff who are trained in the subtleties of the CW application process and the fingerprint report requirement, the TC program has been able to reduce the probability that independent applications contain errors. Implementation of the TC program has allowed many applicants who were previously unable or unwilling to seek one-on-one support to complete the application process to do so. Hence, the program has reduced errors and made the process faster.

The significance of the process improvement brought about by implementation of the TC program can be seen when comparing it to the improvement accomplished by another initiative aimed at a portion of the applicant pool. The Division of Licensing has recently implemented an initiative to expedite CW license applications from members of the military and military veterans. The initiative calls for placing applications by current or former members of the military at the top of the processing queue when they are received. While our analysis shows that the military expedite initiative has indeed been effective at speeding up the process for its beneficiaries, it results in processing speeds that are only 2–3 days faster on average than other applicants.

Another noteworthy facet of the TC program are the benefits—in terms of improved outcomes—to applicants who submit their applications through the other two available methods and therefore have no direct contact with TCs. These spillover benefits are best illustrated in Table 3. Take for example applications submitted at the regional offices. Prior to the implementation of the TC program, processing times for these applications were in the range of 11 days, on average. After implementation of the program, processing times decrease to an average of 6 days, which is comparable to applications received by the TC's offices. Similarly, applications sent by mail had processing times of 32 days on average prior to implementation of the program, yet after program implementation, processing times were reduced to 15 days on average. These improvements are consistent with observations by Miller (2014), who argues that when public-sector organizations reduce processing errors and can change operations to do the same process simultaneously or in parallel, increased processing speeds will be achieved. Reducing errors and eliminating process bottlenecks improve the capacity of government agencies.

One other noteworthy feature shown in Table 3 is the similarity across all outcomes between applications submitted at the TC's offices and the regional offices after the implementation of the TC program. The service level achieved by both types of entities—one a local government entity and

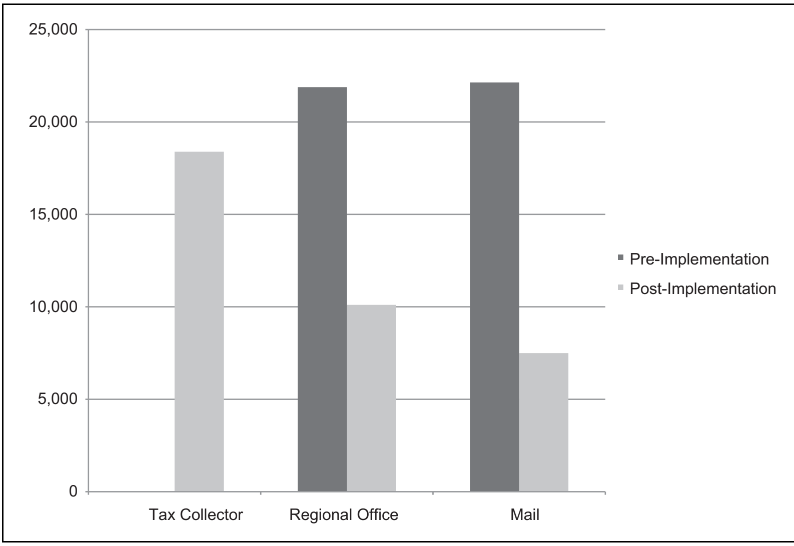


**Figure 8.** Number of concealed weapons license applications in the 11 participating counties before and after the implementation of the tax collector program, by type of entity that received the application.

the other a state government entity—is statistically the same. The processing lengths and error probability that applicants encounter at these two types of locations are equivalent. Therefore, one conclusion that could be drawn is that the TC program effectively leverages the resources of local governments and allows the state agency in charge of CW licensing to open what are in the eyes of their stakeholders many regional offices, without the need to invest the resources that would be required to open real offices. The policy, therefore, is achieving the objective of improving service quality by maximizing the use of human resources at the TC offices and provides an illustration of the effectiveness gains possible through collaboration between local and state government entities.

The benefits brought about by the program have not gone unnoticed by the public. In fact, applicants who have access to the TC program have taken advantage of the opportunity to submit their CW license applications at their local TC's office. Figure 8 shows that by and large applicants have switched to TC's offices as the preferred location, while applications at both regional offices and through the mail have decreased by more than half in the 11 participating counties. While the quicker application turnaround may have been noticed by individual applicants and information about the quickness of the process may have been spread through word of mouth, the more likely reason for the strong shift from mail and regional office applications to TC's offices is the high convenience of these locations as perceived by individual citizens.

The TC program described in this article is just one of several strategies that can reduce error rates in licensing applications. Other policies or programs that could achieve a similar outcome include Internet submission of applications accompanied by a computer program to check for errors. Similarly, the state could set up kiosks with automated equipment in county TC offices that could help reduce or eliminate human intervention to improve processing times at a reduced cost.[8]

While the case documented in this study is specific to the CW program, it is very likely that similar improvements can be achieved in other contexts. A particularly effective case could occur when the process in question involves a state agency that processes and awards many licenses or permits, and these applications are subject to a high error rate or require the submission of sensitive documentation. CW license programs in other states are obvious candidates for benefiting from this type of arrangement. Federal programs that suffer from large backlogs and offer restrictive locations, such as immigration and naturalization application processes, could also benefit from similar arrangements with state or local governments. Local governments will also benefit by maximizing the use of their physical and human resources as well as offering an opportunity to raise additional revenue in the form of convenience fees. Analysis of improvements in local public capacity is an area that merits further research.

## Authors' Note

Authors are listed alphabetically; no senior authorship is implied. Public policy discussions surrounding firearms in the United States have come to the forefront in recent years as a response to multiple mass shooting events in schools (e.g., Columbine, Sandy Hook, Virginia Tech, Parkland) and other public places (e.g., Pulse night club, Vegas strip, Sutherland Springs First Baptist Church, Charleston Emanuel AME Church). These discussions circle around a debate on how to best prevent these types of mass violence, with some groups advocating tightening restrictions in the purchase and possession of firearms as a means to reduce these events, while others advocate easing existing restrictions for the same purpose in addition to "hardening" of schools and other "soft" targets, arming teachers, and other school personnel. Similarly, there is a larger policy debate on ways to address mental illness and the relationship between mental illness, high-risk behaviors, and gun violence. Weighing in on these important policy debates is not the objective of this study. Instead, this study presents evidence on the improvement of outcomes in a government licensing program brought about by a new policy that allows local governments to collaborate with the state government. The fact that the licensing program happens to be for concealed carry of firearms should not be taken as endorsement of any position surrounding this debate.

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## Notes

1. In 2005, 139 full-time equivalent positions were available to process 41,923 new concealed weapon (CW) applications. In 2016, 243 full-time equivalent positions were available to process 244,726 new CW applications.
2. Capacity is also interpreted as a government entity's ability to effectively plan, budget, and evaluate (Greasly, John, & Wolman, 2011) and the ability to be proactive and able to anticipate changes that will lead to informed decisions regarding policy (Honadle, 1981).
3. The 11 counties include Pinellas, which launched the tax collector program on September 2014; Highlands, launched on September 2014; Nassau, launched on October 2014; Lee, launched on April 2015; Marion, launched on April 2015; St. Johns, launched on May 2015; Seminole, launched on September 2015; Hardee, launched on September 2015; Escambia, launched on December 2015; Collier, launched on January 2016; and Lake, launched on February 2016.
4. While most applications take a few weeks or less to be processed, applications with problems such as those from individuals with criminal records, history of mental illness, history of addiction, or similar issues may take a long time to process as the licensing agency conducts a more thorough investigation. In other

cases, an incomplete application or an application with a mistake will be sent back to the applicant, and the applicant may take months or even years before correcting the issue and resending the application. Applicants who are denied a license may also appeal the decision, which would result in a long delay the process.
5. We can also consider attributes of an applicant such as age, education, and so on and/or attributes of the person who process the applications such as experience, individual workload, and also attributes of the processing center such as directing a team to work exclusively on the CW permits, adding more personnel to work on processing CW permits or prioritizing CW permit processing and so on. We cannot control for these factors as we are limited by the data set.
6. We used the zinb command in Stata.
7. We used the psmatch2 command in Stata and derived the common support graphs (psgraph) and the covariate imbalance test (pstest).
8. We thank an anonymous reviewer for this suggestion.

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