Explaining ICE’s Problematic IMAGE: A Public-Private-Partnership in Immigration Policy

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Abstract

This study illustrates the local consequences of participation in IMAGE, a public-private partnership (PPP) by Immigration and Customs Enforcement (ICE). Through IMAGE, ICE’s Mutual Agreement between Government and Employers program, employers sign agreements to assist ICE in determining whether their employees have any immigration violations. The study examines IMAGE through the lens of public-private partnership (PPP) theory within public administration. It concludes that the privacy implications of IMAGE and the harsh punishments enforced on individuals ensnared in the program merit a scrutiny the program has yet to receive. In addition, this study uses data from a Freedom of Information Act request to determine whether participation in IMAGE leads to more arrests. The results indicate that ICE makes more arrests in communities where more employers have an IMAGE agreement. ICE also makes more arrests in communities that adopt so-called sanctuary policies.

Keywords: Immigration Policy, Public-Private-Partnerships, Policy Implementation, Administrative Ethics
Introduction

On June 19, 2018, Immigration and Customs Enforcement (ICE) agents raided three meat processing sites in Massillon, Canton, and Salem, Ohio. They arrested 146 immigrants. All three of the plants were owned by the Ohio-based Fresh Mark company. One important, largely unreported detail about the event is that Fresh Mark was the first Ohio business to participate in ICE’s little-known public-private partnership (PPP): the ICE Mutual Agreement between Government and Employers program (Phillips 2018).

Through IMAGE, as it is known, employers sign agreements to assist ICE in determining whether the business’s employees have immigration violations. Among the many features of IMAGE, employers receive ICE training to evaluate a potential employee’s immigration status. They also promise to screen all employees’ personal information through the Department of Homeland Security’s (DHS) E-Verify system, a program designed to determine whether individuals are eligible for employment.¹ In exchange, ICE agrees to wave potential fines for employers with undocumented workers along with other benefits to the business (Lin n.d.). The growth of IMAGE comes at a time when enforcement actions against businesses and employers—as opposed to immigrants—is dropping nationally (Transactional Records Access Clearinghouse [TRAC] 2019a).

IMAGE is a public–private partnership (PPP). Most scholars define PPPs as formal agreements between government agencies and private actors (typically for-profit businesses) to cooperate in implementing public policies (Linder 1999). Although there are some benefits to PPPs, scholars also note major ethical implications to such agreements (Brinkerhoff and Brinkerhoff 2011). This is particularly true for immigration enforcement PPPs. IMAGE distributes a harm, not a community service, to its target population of undocumented immigrants. In fiscal year (FY) 2017, ICE made 16,654 noncustodial arrests, similar to those made at the Fresh Mark plants in Ohio (TRAC 2018a).²

Political scientists and economists have demonstrated that anti-immigration sentiment increases for reasons that are largely unrelated to immigrants themselves (Newton 2005). For example, it is common to blame immigrants for problems such as unemployment or “taking jobs” from US citizens, despite the fact that most research finds immigration to be a net positive for economic growth (Boubtane et al. 2016; Sequeira et al. 2020). Public support for punitive immigration policies that emphasize detention and removal of immigrants increased following the 2016 election and the rise of populist movements in the western hemisphere (Levy et al. 2016; Norris et al. 2019). This resulted in a zero-tolerance policy under the Trump administration, increasing the rate of immigrant removals from the country compared to the decline at the end of Obama’s term in office (Schreckhise and Chand 2020; Bennett 2017).³ IMAGE fits within this zero-tolerance policy environment.

This study seeks to illustrate the local consequences of participation in IMAGE, particularly the impact the program has on immigrant communities. My analysis suggests a positive relationship between noncustodial arrests and the number of formal agreements between IMAGE and private

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¹ ICE’s explanation of IMAGE can be found on its website (see source ICE n.d.-a).
² See TRAC (2018a) database for data on ICE arrests. Dependent variables for this study are specifically the “noncustodial arrests.”
³ Immigration and Customs Enforcement (ICE) and US Border Control Services (BCS) use the term “removal,” as opposed to the generalized term deportation. Throughout this paper I use the term “removal,” as opposed to “deportation,” because the former is the legal term used by enforcement agencies (Law 2014).
employers, called memorandums of agreement (MOAs). Rates of noncustodial arrests are significantly higher in communities with IMAGE MOAs. Noncustodial arrests are also elevated in communities that adopt anti-detainer—otherwise known as “sanctuary”—policies, indicating that ICE may be using direct enforcement mechanisms in less-cooperative communities.

**Immigration Enforcement, Cooperation, and IMAGE**

Interior US immigration enforcement is a complex topic, frequently misunderstood by even those who study immigration policy. Contributing to the confusion is the fact that no one agency is entirely in charge of enforcement, although Immigration and Customs Enforcement (ICE) is the agency that detains and processes immigrants for removal. As such, ICE rightly receives the most attention from critics of US policy (Markowitz 2019). However, ICE agents are not the only government actors to play significant roles in immigration enforcement. For example,

- Customs and Border Protection (CBP), ICE’s partner agency under the Department of Homeland Security (DHS), is in charge of immigration enforcement at US ports of entry and within 100-miles of the border (Robbins 2014);
- The Executive Office of Immigration Review (EOIR) oversees immigration court and is housed in the Department of Justice (DOJ);
- US Citizenship and Immigration Services, also part of DHS, is in charge of visa and citizenship applications; and
- The Office of Refugee Resettlement is housed in the US Department of Health and Human Services.

These are just some of the federal agencies involved in immigration enforcement. With the Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) of 1996 and subsequent federal policies, state and local law enforcement agencies have played increasingly larger roles in helping to enforce federal immigration policy. Needless to say, fulfilling ICE’s mission requires some extra-organizational cooperation.

More than anything, ICE relies on extra-organizational cooperation to find and, ultimately, detain immigrants that are “eligible” for removal. The need for cooperation is partly due to the legal gray area in which so many immigrants find themselves. Technically speaking, any immigrant without legal authorization to live in the United States, i.e., a current visa, can be subject to removal (Kelly 2017). However, since lacking documentation is not a crime, but an administrative violation, most undocumented immigrants are unlikely to end up in ICE’s custody—unless they first end up in the custody of law enforcement. Thus, immigrants who are detained and find themselves in removal proceedings are typically handed to ICE via cooperative federalism programs, such as ICE’s largest program, Secure Communities (S-Comm).

Established in 2008, S-Comm is essentially a nationwide immigrant screening program that co-opts local and state law enforcement agencies, primarily county sheriff offices, into conducting immigration background checks on individuals in their custody. For decades, the biometric information of individuals arrested by state and local law enforcement was shared with the Federal

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4 The IIRIRA of 1996 created a category of documented immigrants who can be subject to removal if they have committed specific crimes under the category of “aggravated felonies” (Morawetz 2000).
Bureau of Investigations (FBI) for criminal background checks (e.g., to determine if an individual had outstanding warrants). S-Comm requires the same biometric information be forwarded to DHS, where ICE can check to see if the individual has any immigration violations. If ICE agents flag an individual as an undocumented immigrant, they can—and typically do—issue a detainee requesting the jail hold the person until ICE can obtain the individual and begin a removal proceedings. Since most people arrested are booked in county jails, county sheriffs are vital to S-Comm’s implementation (Chand 2020; Farris and Holman 2017).

A much smaller, although equally controversial, ICE cooperative federalism program is 287(g). Lacking a legal status is not a criminal offense. Hence, street-level law enforcement agents (e.g., cops and sheriff deputies) are unable to detain or even interrogate an individual solely for immigration purposes. Yet 287(g), named after the section of the IIRIA (1996) that created the program, allows participating officers to receive ICE training, designating them to perform such immigration duties. Unlike S-Comm, state and local law enforcement agencies must sign memorandums of agreement (MOA) with ICE to participate (see ICE n.d.-b).

A significant number of ICE arrests and removals also come through cooperation with state and federal prisons. ICE can identify immigrants eligible for removal (either because they are undocumented or they committed a crime causing them to lose legal status) by screening individuals in prisons through its Criminal Alien Program (CAP) (American Immigration Council 2013).

Because immigrants arrested by ICE through programs such as S-Comm, 287(g), and CAPs are initially taken into custody by a separate law enforcement agency, individuals detained by ICE through these cooperative federalism intergovernmental programs are classified as “custodial arrests,” meaning the custody of the individual is simply transferred from one agency (e.g., a local jail) to ICE. These custodial arrests constitute most ICE detainments, with more than 80% of custodial arrests coming through S-Comm (TRAC 2018b; TRAC 2019a).

IMAGE, however, takes ICE’s cooperative enforcement into the new territory of partnerships with private entities. As previous studies have noted, S-Comm and 287(g) have blurred the line between immigration policy and criminal justice, which has had the effect of criminalizing immigrants in the minds of many Americans (Garcia Hernandez 2016). Although ICE claims S-Comm was designed to target “serious criminals,” only 3.3% of individuals removed through the program in its first several years met IIRIRA’s definition of “aggravated felony.” Most had only minor criminal violations such as driving without a license or misdemeanor drug possessions or no criminal convictions whatsoever, and thus were removed simply because of civil immigration infractions (TRAC 2012). Yet IMAGE does not even bother with the presumption, no matter how inaccurate, that immigrants being detained through it have committed some type of criminal violation. Instead, IMAGE enlists private businesses to essentially tattle on their own employees, and in exchange, the business receives civil immunity from fines or liability for hiring undocumented immigrants.

IMAGE was created in the latter half of the George W. Bush administration in 2006. Through IMAGE, ICE partners with private employers to screen the immigration status of a company’s employees just as S-Comm screens the background of individuals booked in state and local jails.

5 Although S-Comm meets the scholarly definition of a “cooperative federalism” program, ICE has stated that participation in S-Comm is automatic, and jurisdictions cannot “opt out” when a jail submits biometric information to the FBI for background checks (Vedantam 2010). Local and state jails can refuse compliance with ICE detainers, which has upset conservative organizations who often refer to these as “sanctuary” jurisdictions (see Vaughan and Griffith 2020 for an example).
The business signs an agreement with ICE in which it agrees to a series of screening procedures that verify an employee’s legal immigration status. These procedures include an annual internal inspection of form I-9 files, which new hires fill out to establish their employment eligibility (ICE n.d.-a).

Some of the details on the IMAGE process include:

- Screening all applicants through E-Verify, a federal online program that allows employers to check the validity of form I-9 information;
- Commissioning annual secondary I-9 audits by external firms or trained employees;
- Creating and annually updating an internal training program to detect fraudulent documents;
- Establishing procedures for reporting to ICE any violations or discrepancies discovered;
- Instituting a protocol for responding to no-match letters issued by the Social Security Agency (SSA);
- Providing a tip line by which employees can report unauthorized workers;
- Submitting annual reports to ICE to track results from participation in IMAGE; and
- For businesses with 50 or more employees, designating a compliance officer that monitors the business’s compliance with IMAGE (National Immigration Law Center [NILC] 2007).

Finally, once a year the business must report the number of individuals it fired or denied employment as a result of IMAGE participation. “IMAGE participants are required to immediately report to ICE the discovery or allegations of any substantive criminal violations” (NILC 2007).

In return, ICE provides several benefits, some of which are admittedly token, e.g., being recognized as “IMAGE certified.” A significant benefit to the business, however, is immunity from liability. IMAGE partner businesses are promised no Form I-9 audits for a minimum of four years. An I-9 audit can be devastating to an employer, especially small businesses. They can force a company into bankruptcy. ICE uses I-9 audits for both criminal and administrative investigations. In addition to criminal sanctions, an employer can be fined up to $16,000 for each undocumented immigrant employee and receive federal debarment, which excludes the company from receiving federal benefits or being awarded federal contracts (ICE 2019).

When DHS unveiled IMAGE, it also published new rules altering an employer’s legal liabilities for not firing an employee that company management believes to be undocumented (NILC 2007). In the past, an employer was under no obligation to immediately fire an employee upon reception of a no-match letter from the SSA (i.e., an employee’s personal information does not match SSA records). The mismatch can be a simple mistake. Even the SSA characterizes its no-match letters as opportunities to correct errors, not grounds for termination (NILC 2019). However, under a new rule, issued by DHS in June 2006, employers face civil fines ($10,000 per violation) or prosecution if they do not fire or rectify the SSA check within 90 days of receiving a no-match letter (Aldana 2008, 1,099–1,100).

Early evidence indicates that many employers responded to the rule by reflexively firing employees and in some cases, reporting them to ICE out of fear of being found liable for knowingly hiring unauthorized workers. This approach further exacerbates the already difficult situation for undocumented workers and their families. 

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6 Quoting the NILC, “The SSA itself advises employers not to take adverse action against an employee named in a no-match letter” (see NILC 2019).
undocumented workers (NILC 2019). Employment attorneys noted that the DHS regulatory change, “provided a safe-harbor procedure for employers in receipt of a no-match letter: if an employer ‘take[s] reasonable steps’ to resolve the discrepancy within fourteen days of receiving the no-match letter, the employer will avoid any risk of the DHS finding he had ‘constructive knowledge’ that the employee was not authorized to work in the United States” (Gibek and Shteierman 2007, 27).

IMAGE remained relatively small within its first several years, with only slightly more than 100 businesses enrolled nationwide by 2011 (Brumback 2011; Overman 2011). Still, it effectively ensnared a number of immigrants, the vast majority of whom committed no criminal infractions and were likely no danger to their communities, as immigrants, both documented and undocumented, are no more likely to commit crimes than US citizens (Orrenius and Zavodny 2019). Evidence also suggests that early business enrollees may have been muscled into signing IMAGE agreements out of fear of being audited or raided by ICE (Aldana 2008, 1,098). For example, in December 2006, ICE agents raided meatpacking plants in six states run by Swift & Company, at the time the world’s second-largest meat processing company. Some 1,300 employees were arrested, roughly 10% of the company’s workforce, which effectively shut down the business for a short period (Hsu and Williams 2006; Waltz 2018). The raids, dubbed by ICE as “Operation Wagon Train,” were at the time the largest single workforce raid action in history (Kammer 2009).

Immediately after the Swift raid, other meatpacking and food processing companies signed IMAGE agreements. In January 2007, ICE arrested 21 workers at the world’s largest slaughterhouse in Tar Heel, North Carolina, owned by Smithfield Packing Company. This was a much smaller enforcement action. Company representatives noted the arrests did not disrupt the plant’s business. “There were no helicopters or buses or even anybody in uniforms. It was done in an orderly, professional fashion,” noted a Smithfield spokesperson (Preston 2007). ICE agents had been alerted through Smithfield’s IMAGE program.

Smithfield management specifically mentioned previous raids, such as the Swift operation, as motivation for participating in the program. News reports of the arrests cited a Smithfield spokesperson calling the decision to participate in IMAGE “a business decision,” the result of “an implied threat” (Fears and Williams 2007). The company’s executive vice president characterized the company’s participation by saying, “we’re being a good corporate citizen and complying with the federal law. When the raids occurred, we saw the writing on the wall” (Walzer 2008).

Representatives of the United Food and Commercial Workers Union (UFCW) accused Smithfield of participating in IMAGE to discourage workers from unionizing. As evidence, they pointed to findings by the National Labor Relations Board, citing Smithfield for attempting to intimidate immigrant employees in the past. UFCW also noted that some leaders of a recent unionizing effort were among the names of employees turned over to ICE via IMAGE (Fears and Williams 2007).

IMAGE remained relatively small and obscure during the Obama administration. Not one major news outlet mentioned the program throughout his presidency.⁷ In FY 2011, ICE spent only about $7 million on IMAGE (Brumback 2011). However, the Trump administration placed a heavy emphasis on workplace raids and sought to increase participation in IMAGE (Griffith

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⁷ Lexis-Nexis search with the Obama presidency dates (Jan. 20, 2009 to Jan. 20, 2017) produced only two news articles that mentioned the program, both published in regional newspapers.
and Gleeson 2019, 489). By September 2018, there were 566 individual local IMAGE employers operating in 204 counties nationwide.\(^8\)

The uptick in IMAGE participation may also have been a result of the Trump administration’s greater emphasis on noncustodial arrests, sometimes called community arrests. As opposed to previously discussed ICE arrests, in which ICE receives custody of an immigrant from a law enforcement agency through programs such as S-Comm, noncustodial arrests occur when ICE directly takes an individual into custody (i.e., arrests) without another law enforcement agency first detaining the individual (TRAC 2019b). These arrests, which increased notably during the Trump years (TRAC 2018b), can occur in diverse places and by various means: a workplace raid, a scheduled court appearance, a US Citizenship and Immigration Services appointment, or even at the individual’s home if ICE has the person’s address.\(^9\)

ICE’s primary means of making noncustodial arrests is through workplace raids. Arrests made possible by IMAGE PPPs are noncustodial arrests; although ICE does not report what percentage of noncustodial arrests are made possible by IMAGE. Figure 1 below, displays a pie chart breaking down all identifiable ICE arrests for the first three quarters of FY 2018 (October 2017 through June 2018). The majority (69%, noted in blue on the chart) are custodial arrests through programs such as S-Comm, 287(g), and CAPs. However, a significant minority, 25%, are direct noncustodial arrests, made possible by programs such as IMAGE.

In the following section, I discuss the literature on PPPs, focusing on those established for information-sharing purposes, such as IMAGE. I also explain why IMAGE—as opposed to many other information-sharing PPPs—poses serious ethical problems.

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\(^8\) From the author’s Freedom of Information Act (FOIA) request on the program. Note that the 566 number is a count of local employment places.

\(^9\) The Biden administration has stopped ICE arrests at courthouses, which happened with some frequency during the previous administration (see Katkov 2021).
PPPs, Information Sharing, and Administrative Ethics

Public-private partnerships are nothing new. In some of the earliest civilizations of which we have records, such as ancient Babylon and Greece, governments partnered with private sectors to accomplish certain public tasks (Giti et al. 2019, 14). Within the last several decades, PPPs have become an increasingly popular solution to modern pressures on policymakers, particularly in the Western world, to shrink government and run it more business-like. Putting aside the myth of private-sector efficiency, PPPs are a modern reality and universally used the world over. Despite their ubiquity and the uptick in scholarly attention to them, there is not widespread agreement on how to define PPPs (Roehrich et al. 2014).

However, it appears that practically all scholarly definitions of PPPs contain at least two components:

1. A formal cooperation agreement between a government agency and private actor(s), and
2. The intent to implement at least some aspect of public policy (Linder 1999).

In this study, I am working from the broadly defined description of PPPs as “cooperative institutional arrangements between public and private sector actors,” (Hodge and Greve 2007), which satisfies all the working definitions within the scholarly literature on the topic.\(^\text{10}\) Most scholars, this author included, would also separate contracted services from PPPs, although there are notable exceptions (e.g., Kettl 1993).

Brinkerhoff and Brinkerhoff note that given their broad popularity in use and study, “No single analytic framework can capture the diversity, relevant parameters, and qualities of PPPs” (2011, 5). Indeed, PPPs expand the gamut of policy issues, including healthcare (Joudyian et al. 2021), environmental protection (Van Ham and Koppenjan 2001), agriculture (Spielman et al. 2010), and education (Verger 2012). While surprisingly few scholars have examined immigration policy through the PPP framework (see de Graauw 2012 for the one case of which I am aware), business partnerships with federal, state, and local governments to enforce immigration policy are quite common in the twenty-first century. Notably, privately operated immigration detention facilities have become a multi-billion-dollar industry (Doty and Wheatley 2013).\(^\text{11}\)

Policymakers adopt PPPs for a wide variety of reasons. IMAGE best aligns with PPPs developed for information-sharing purposes like those in national security policy (Givens and Busch 2013; Carr 2016). Information-sharing PPPs are “relationships involving the sharing of power, work, support, and/or information with others for the achievement of joint goals and/or mutual benefits” (Kernaghan 1993, 61). Accurate information regarding immigration status is critical to ICE’s ability to fulfill its mission. Immigration enforcement is similar to criminal justice policy in that administrators implement a punishment (e.g., arrest and detention), but it is fundamentally different from enforcing criminal statutes for the primary reason that one’s immigration status is not a matter of criminal law. Lacking documented status is not a crime and is certainly not a visible act one commits. Thus, ICE has come to rely on cooperation from other actors who can inform the agency of an individual’s immigration status. For most individuals detained and removed (e.g., those detained through custodial arrests), ICE relies on partnerships or cooperation with local government offices, such as those in the S-Comm and 287(g) programs.

In fairness to immigration enforcement officials, information sharing is a necessary reality of enforcing immigration policy. Obviously, ICE needs to share information with its sister agency, Customs and Border Protection (CBP), both of which fall under DHS, for the simple reason that they are enforcing the same area of policy. It is also arguable that the broader mission of DHS could not be accomplished without information sharing across government agencies at federal, state, and local levels (see Givens and Busch 2013 for one such argument). Information inaccuracies have plagued many of ICE’s enforcement programs since the agency’s inception. In the first year of S-Comm’s operation, the program’s IDENT database miss identified more than 5,800 individuals as undocumented immigrants, this when the program was only operating in roughly one-third of the country (Preston 2009). At least one US citizen was improperly held by ICE for 3.5 years while the agency insisted the man was an undocumented immigrant (Bekiempis 2014). A 2011 study using a random sample of individuals flagged as undocumented immigrants through S-Comm found that 1.6% of individuals are actually US citizens and approximately 3,600 US citizens had been improperly arrested by ICE (Kohi, Markowitz, and Chavez 2011).

\(^{10}\) At least all “known” definitions to this author.

\(^{11}\) Admittedly, some could consider private detention as a simple contracted service as opposed to a PPP. However, because private employees of a company are implementing a public service (detention), which comes into contact with private residents, and doing so in substitute of what are typically public employees (prison guards), the author considers private detention as an example of a PPP.
Moreover, information sharing across government and private sector organizations is often essential to accomplishing public goals. In our increasingly interconnected world, the spread of infectious diseases has highlighted a need for information sharing PPPs to respond to pandemics (Katz et al. 2018). Even prior to COVID-19, global health NGOs touted the need to develop information-sharing networks between government and private actors with clear lines of communication and protocols to mitigate outbreaks (UN World Food Programme 2017). Today, all parties—public, private, and nongovernmental—agree that information sharing across the public and private sector is more critical than ever to identify cases, track disease’s spread, and successfully distribute tests and vaccines (Alexander 2020; Wiseman 2020).

However, what separates PPPs in public health from immigration policy is that the latter delivers harms or burdens (e.g., detention and removal) to the intended target population, as opposed to benefits such as tests and vaccines for viruses (Schneider and Ingram 1993). In their seminal work on social construction theory, Schneider and Ingram (1993) define undocumented immigrants as a “deviant” group, meaning a group with a negative public image and little to no political power. Such groups typically receive burdens (harms) when they are the target population of a policy. If there is a “service” or benefit within IMAGE, it is the benefits distributed to the business owners, defined as an “advantaged” group in the American political system. These are actors with high power and strong positive public image and, thus, are typically successful at negotiating for benefits in the policymaking process. By contrast, immigrants, especially undocumented ones, are a low-power community with little recourse to respond to government or business policies that inflict pain on themselves or their community.

Furthermore, unlike the information sharing that takes place between ICE and CBP, or even the cross-governmental information network programs such as S-Comm, the sensitive information flowing to administrators via IMAGE is held by private actors. Cooperative federalism partnerships, such as S-Comm, are fraught with their own controversies and challenges (see Chand 2020; Farris and Holman 2017; Schreckhise and Chand 2021). However, IMAGE increases the agency’s access to information on individuals’ immigration statuses without the necessary cooperation of local agencies. Local government agencies that play a disproportionately large role in implementing S-Comm, such as sheriff offices, respond to public pressures. Private businesses, however, are largely immune from public political sentiment.

This creates serious issues of ethics and accountability. While there are strict rules limiting government agencies’ handling of immigration data, there are no such limitations on private actors. The actions of private businesses receive far less public scrutiny. Business owners and managers are not elected and do not answer to elected policymakers, as public administrators do. Thus, there is far less public oversight of IMAGE than ICE’s other enforcement programs such as S-Comm and 287(g), which have received tremendous public (e.g., American Civil Liberties Union [ACLU] 2010) or scholarly scrutiny (e.g., Armenta 2012; Chand and Schreckhise 2015).

Even in traditional PPPs, the lines of accountability are not always clear. Forrer and his colleagues (2010) note that PPPs replace the vertical principal-agent relationship, between elected policymakers as the principals (e.g., President and Congress) over public administrators (agents) with a horizontal relationship between administrators and private actors. However, while the lines of accountability are blurred within traditional PPPs, they are practically invisible for IMAGE. Given that IMAGE facilitates the sharing of extremely sensitive information about private residents—including US citizens, not just immigrants—between private businesses and ICE, there are
tremendous privacy implications to the program. The privacy rights of all employees are potentially compromised. One of the stated purposes of IMAGE is to reduce identity theft. Ironically, the program may well increase such fraud. The passing of sensitive information between different layers of government and private businesses potentially increases the likelihood of theft, as data could end up in the wrong hands (Brown 2005, 243). Similarly designed information-sharing PPPs involving national security policy, implemented during the height of the War on Terror, drew intense scrutiny over privacy rights from civil libertarians. Consequently, significant privacy checks were created for those programs (Carter 2008). Such privacy checks have yet to be implemented for IMAGE.

The following section explains how this study empirically examines the impact of IMAGE, testing whether the presence of the program increases ICE’s local noncustodial arrests.

**Data and Hypotheses on Cooperation**

Through a Freedom of Information Act (FOIA) request of ICE, the author was able to obtain the names and addresses of all employers participating in IMAGE up to Sept. 27, 2018. Nationally, 566 local employers signed memorandums of agreement (MOAs) to participate in the program. ICE enforcement data (e.g., arrests and removals) is reported at the county level due primarily to the fact that most of ICE’s enforcement programs, such as S-Comm, require participation of county sheriff offices that run county jails (Chand 2020). Thus, this study uses a county-level unit of analysis. This is a cross-sectional analysis with most right-hand-side variables, other than those noted, from 2017.

For this study, I have created an IMAGE MOAs variable that indicates the number of IMAGE-participating businesses in the county at the time of the FOIA-response date. While IMAGE is a relatively small program compared to S-Comm, Figure 2 below illustrates the size of the program under the Trump administration. The map displays the location of IMAGE agreements by county in the continental United States according to the ICE FOIA response. By 2018, there were 204 IMAGE MOAs—mostly concentrated in larger urban counties or those with comparably large Hispanic populations.

Because immigrants detained directly by ICE are noncustodial arrests, I use the county number of noncustodial arrests to create two noncustodial arrests dependent variables for this study. These variables cover the total number of ICE noncustodial arrests in the county for FY 2017 and the first eight months of FY 2018 (collected via TRAC 2018a). The two dependent variables are regressed against the same cross-sectional model. With respect to participation in IMAGE, I hypothesize:

\[ H1: \text{The likelihood of noncustodial arrests increases with the number of IMAGE MOAs, ceteris paribus.} \]

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1 Federal FY covers October 1 (of the preceding calendar year) through September 30. For example, FY 2017 covers Oct. 1, 2016 through Sept. 30, 2017. The FY 2018 dependent variable covers Oct. 1, 2017 through May 31, 2018, as TRAC was only able to obtain the first eight months of enforcement data.
As discussed in the previous section, ICE requires a certain level of cooperation from law enforcement offices to implement many of its enforcement programs. I use three measures to indicate the level of cooperation ICE receives from local law enforcement agencies. For example, law enforcement participation in 287(g) appears to significantly increase the number of removals from counties through S-Comm (Chand 2020). I use a count variable of the number of 287(g) MOAs with local law enforcement agencies within the county (Immigration Legal Resource Center 2020). Regarding this variable, I posit:

\[ H_2: \text{The likelihood of noncustodial arrests will increase with the number of 287(g) MOAs, ceteris paribus.} \]

Additionally, some have argued that the number of local intergovernmental service agreements (IGSAs) to detain arrested immigrants between ICE and local and state jails is also significantly related to ICE removals (Jaeger 2016). I use a count variable that measures the number of immigrants (in units of 100) IGSA facilities in the county are contracted to detain for ICE, labeled IGSA capacity per 100 (TRAC 2015). I posit that:

\[ H_3: \text{The likelihood of noncustodial arrests will increase with the capacity of ICE to detain immigrants in IGSA facilities within the county, ceteris paribus.} \]
This study examines specific ICE direct enforcement actions: noncustodial arrests. For these enforcement actions, ICE is not relying on the cooperation of local and state government agencies. Of particular concern is ICE’s participation with private businesses through IMAGE. However, ICE also frequently makes these arrests through raids of immigrant-employing businesses that do not participate in IMAGE as well as other locations. Because local government is unable to interfere with ICE’s ability to make direct noncustodial arrests, many have argued that ICE steps up its noncustodial arrests in areas where there is opposition to traditional enforcement programs such as S-Comm (CHR 2018; TRAC 2019b). Notably, many communities and local law enforcement agencies have adopted formal policies specifying that they will limit cooperation with ICE detainers.

Starting in January 2017, ICE began issuing reports (called Declined Detainer Outcome Reports) on these so-called “sanctuary” communities, indicating whether a municipality or law enforcement agency (typically the county jail) had a policy of non-compliance with some ICE detainers. These reports were ICE’s attempt conform with President Trump’s Executive Order 13768. The first of these reports, issued in February 2017, is used for this paper (US ICE 2017, 23–35). During S-Comm’s tenure under President Obama, 196 counties adopted formal policies limiting cooperation with ICE detainers (ICE 2017). I use a dichotomous variable with the label anti-detainer policy noting these counties. The anti-detainer policy variable also includes counties in California, which passed the Trust Act (2014) that limited the ability of county officials in the state to comply with some ICE detainers (ACLU of Northern California n.d.).

While one may presume these policies would reduce the number of ICE enforcement actions in a community, it is important to note that these policies were passed to limit cooperation with S-Comm. They do not limit direct ICE enforcement actions, including noncustodial arrests. Even if a county jail refuses to honor an ICE detainer and hold an individual for ICE, there is nothing to stop an ICE agent from directly arresting the individual in the community after he or she is released by local law enforcement. Municipal governments or local law enforcement agencies cannot stop ICE from directly detaining an individual, and ICE has explicitly stated it seeks to increase direct enforcement actions in sanctuary communities (Center for Human Rights [CHR] 2018; Miroff and Barrett 2020).

Thus, I make the following hypothesis about the effect of anti-detainer policies:

**H4:** Counties with anti-detainer policies will experience significantly more noncustodial arrests, ceteris paribus.

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13 “Sanctuary” community is essentially shorthand for describing a jurisdiction that has limited cooperation with ICE detainers. The ICE (2017, 23–35) report used here explains the circumstances in which a local agency, the majority of which are county jails, will not honor an ICE detainer. For example, common limits on compliance with detainers includes not holding immigrants beyond their release date if the charges are dropped or requiring a judicial warrant in addition to a detainer.

14 ICE only ended up publishing three of these reports. The reports contained an updated list of agencies that did not comply with a specific detainer and municipalities and agencies that have anti-detainer policies. The latter list is used here.

15 This period is September 2011, the first anti-detainer policy, to December 2014. Obama formally suspended S-Comm at the end of 2014.
ICE Arrests and Control Variables

While there have been no prior studies to predict ICE noncustodial arrests, there has been much research predicting ICE removals through S-Comm in recent years (Chand and Schreckhise 2015; Jaeger 2016; Pedroza 2019; Schreckhise and Chand 2021). I draw from prior research on S-Comm removals to further develop the models used to predict noncustodial arrests. It is logical that some of the variables used to predict S-Comm removals should also be significantly related to noncustodial arrests. For example, while no studies have examined the connections between PPPs and immigration enforcement, recent studies have examined the roles of immigrant-serving organizations (ISOs) in helping protect immigrants from being removed (Calderon et al. 2021).

One particularly pertinent topic in this nonprofit line of research has been the effect of low-cost or pro bono legal aid provided by ISOs. Because an individual’s immigration status is a matter of civil law (not criminal), immigrants facing removal (deportation) hearings in immigration court are not provided with an attorney if they cannot afford one. This is true even for unaccompanied children. Thus, many immigrants, especially detained individuals, go through hearings without legal representation (Eagly and Shafer 2015). While the research on the effects of legal aid in civil hearings, such as immigrant cases, is far from definitive (Greiner and Wolos Pattanayak 2011), there is strong consensus that immigrants with attorneys, or at least some form of professional legal representation, are more likely to win their hearings (Chand et al. 2017; Eagly and Shafer 2015; Ramji-Nogales 2007).16 Scholars have recently demonstrated that regions with more ISOs that provide pro bono and low-cost legal aid experience fewer removals through ICE programs such as S-Comm, all things being equal (Chand et al. 2020).

While the analysis in this paper uses ICE noncustodial arrests, not removals, as the dependent variable, it may be reasonable to assume that legal aid ISOs provide could help immigrants navigate the complex web of immigration policies in a way that helps them avoid falling into the hands of ICE. For this reason, I use a comprehensive database of ISOs nationally (created by Chand et al. 2020) to create a variable labeled ISO index, which is a measure of the concentration of ISOs and available nonprofit legal-aid services in the county. This index is an additive measure that sums five facets of ISOs related to their work providing legal aid:

1. The total number of ISOs in the county17;
2. The number registered to provide pro bono attorneys in immigration court (EOIR n.d.);
3. The number of non-attorney legal aid representatives (DOJ n.d.);
4. A measure of the budgets for all the ISOs in the county (Charity Navigator n.d.; Guide Star n.d.);18

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16 While it is clear that immigrants with legal aid are more likely to win their hearings, debate exists over whether the effects are endogenous (see Eagly and Shafer 2015, 48).
17 Collected from four sources listed in the Bibliography: Catholic Legal Immigrant Network (CLINIC n.d.); the Immigration Advocates Network (IAN n.d.); Executive Office of Immigration Review (EOIR n.d.); and Department of Justice (DOJ n.d.).
18 Composed from the collective Revenue and Expenses for all groups in the county, reported on groups’ Form 990s, accessed via Guide Start and Charity Navigator. Here, I made a percentile measure for each county based on where it ranked in relation to other counties with ISOs. Counties in the highest 75th percentile, meaning they had larger overall ISO budgets than 75% of counties with ISOs, were given a value of 4; counties between the 50th and 74th a value of 3; between the 25th and 49th, 2; between 1st and 24th, 1. Counties with no ISOs were given 0 values.
5. And the number of days through FY 2018 ISOs in the area were registered with the Board of Immigration Appeals (BIA) to provide nonprofit legal aid for immigration hearings (DOJ n.d.).

Of course, demographic factors and socioeconomic conditions will certainly affect the local noncustodial arrest rate. For example, the percent of Hispanics and Latinos in the county are important indicators of local ICE enforcement actions. Studies have also found that the growth of the local Hispanic population is an equally good, if not better, predictor of S-Comm removals (Chand 2020; Jaeger 2016). Such demographic findings support the racial threat model, which argues that punitive policies, such as immigration restrictions, are the result of perceived threat to a social and cultural power group (middle-class whites) from the growth of a dissimilar group (individuals of color) (Key 1949; Rocha and Espino 2009). I test the racial threat model against ICE noncustodial arrests using the US Census American Community Survey's 2017 numbers to develop a % Hispanic population in the county (US Census ACS 2017). To test for growth of the local Hispanic population, I use a 5-year growth rate variable, labeled % Hispanic change, which measures the percent change of the county population from 2012 to 2017 (US Census ACS 2017).

Economic conditions are often an explanation for the adoption and aggressive enforcement of anti-immigration policies. Marxist conflict theory states that restrictions on immigration will be driven by the perceived economic threat immigrants pose to native populations, typically blue-collar workers (Meuleman et al. 2009). This would explain why the local unemployment rate appears to predict the passage of restrictive immigration ordinances and participation in federal immigration enforcement programs (Hopkins 2010; Newman et al. 2012). Whether punitive immigration policies actually help American-born workers is a matter of great controversy. The majority of research demonstrates that immigration is a boon to the economy as a whole (e.g., Boubtane et al. 2016). Yet, there is some research indicating that immigration can detrimentally impact some workers in western countries, notably the wages of blue-collar workers (see Edo 2019 for an excellent review of studies). For this paper, I use two measures of county-level economic hardship to predict ICE noncustodial arrests: the unemployment rate (US Bureau of Labor Statistics [BLS] 2017) and the Gini coefficient inequality index (US Census ACS 2017).

Immigration has become a particularly partisan topic within the last couple of decades (Casellas and Leal 2013). It is abundantly clear that politically conservative communities are more likely to adopt restrictive immigration policies (Lewis et al. 2013; Wong 2012). Research also indicates that ICE removes a greater number of immigrants from counties that vote heavily Republican, all things being equal (Chand and Schreckhise 2015; Schreckhise and Chand 2021). This study tests for the effects of local political ideology with an average of the % Republican vote received by presidential candidates at the county level in 2012 and 2016 (New York Times 2012 and 2016).

Immigration policy has unfortunately become intermingled with traditional criminal justice policy since the IIRIRA (1996). ICE itself, which was established in 2003, maintains that every one of its enforcement programs (e.g., S-Comm, 287(g), and IMAGE) is intended to lower local crime rates. Regardless of ICE’s claims, study after study shows that these programs do nothing to lower the local crime rate and their implementation bears no relationship to local criminal activity (Chand and Schreckhise 2015; Jaeger 2016; Miles and Cox 2014; Schreckhise and Chand 2021;).

19 I took the aggregated number of days all ISOs in the county were registered with the BIA and broke those into percentiles, as with the budget values.
No doubt, this is largely due to the fact that immigrants, documented or not, are no more likely to cause or commit crime than US citizens (Feldmeyer 2009; Moehling and Piehl 2009; Orrenius and Zavodny 2019). Still, ICE markets IMAGE as a program targeted at “criminal activity” (ICE n.d.-c). The analysis here tests the relationship between crime and noncustodial arrests using the county crime rate, which is the number of reported crimes (both violent and property) to county law enforcement agency per 1,000 residents (FBI 2017).

Additionally, immigration enforcement actions are disproportionately focused on border communities, where immigration policy has greater salience (Ellermann 2009). Thus, the models include a dichotomous variable, border 100 miles, indicating whether any part of the county is within 100 miles of the US-Mexico border. Lastly, I control for the county population, expressed in the models by units of 50,000 residents, pop by 50k (ACS 2017).

The following section provides analysis of the above variables and regression models predicting the county noncustodial arrest rates.

**Analysis**

Table 1, below, displays the summary statistics for the number of IMAGE MOAs, the cooperation with ICE variables, and the county demographic variables discussed in the previous sections.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PPPs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IMAGE MOAs</td>
<td>0.18</td>
<td>1.41</td>
<td>0</td>
<td>39</td>
</tr>
<tr>
<td><strong>Cooperation with ICE</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>287(g) MOAs</td>
<td>0.02</td>
<td>0.14</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>IGSA Capacity per 100</td>
<td>0.06</td>
<td>0.65</td>
<td>0</td>
<td>21.17</td>
</tr>
<tr>
<td>Anti-detainer Policy</td>
<td>0.08</td>
<td>0.27</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>County Demographics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ISO Index</td>
<td>1.56</td>
<td>7.49</td>
<td>0</td>
<td>165</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>9.12%</td>
<td>13.71%</td>
<td>0.71%</td>
<td>99.18%</td>
</tr>
<tr>
<td>% Hispanic Change</td>
<td>0.83%</td>
<td>1.46%</td>
<td>-1.25%</td>
<td>5.81%</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>4.60</td>
<td>1.67</td>
<td>2</td>
<td>19.5</td>
</tr>
<tr>
<td>Gini Coefficient</td>
<td>4.48</td>
<td>0.36</td>
<td>3.52</td>
<td>5.98</td>
</tr>
<tr>
<td>% Republican Vote</td>
<td>53.98%</td>
<td>14.52%</td>
<td>7.3%</td>
<td>87.9%</td>
</tr>
<tr>
<td>Border 100 Miles</td>
<td>0.02</td>
<td>0.14</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Crime Rate</td>
<td>782.13</td>
<td>979.2</td>
<td>0</td>
<td>34,086.7</td>
</tr>
<tr>
<td>Population per 50,000</td>
<td>2.04</td>
<td>6.57</td>
<td>0.001</td>
<td>202.11</td>
</tr>
</tbody>
</table>

As the dependent variables for this study are total numbers of arrests by individual counties (ranging from 0 to 1,009), it is appropriate to use count models to predict the outcome (Hilbe 2014).20

20 Alaska, Hawaii, and Puerto Rico are not included due to unavailable data.
There are implications to running this analysis aggregated at the county level. While noncustodial arrests are not uncommon (there were 28,573 in FY 2017 and 2018), they are overwhelmingly located in urban areas with greater concentrations of immigrants. This is not to say ICE rarely arrests or deport immigrants from rural areas. The agency certainly does. However, ICE usually obtains custody of individuals in those areas via traditional custodial arrests. For resource reasons, ICE focuses direct enforcement actions in urban and suburban communities. This fact is illustrated in Figure 3, which displays ICE’s noncustodial arrests at the county level for FY 2017 and the eight months of FY 2018. The vast majority of US counties experienced no (zero) noncustodial arrests in both years. Only 520 counties experienced at least one noncustodial arrest. Only 2% of counties experienced more than 100 arrests, and only 5 counties (0.2%) experienced more than 1,000 arrests over the two-year period.

**Figure 3: IMAGE Non-Custodial Arrests FY 2017–2018**

Source: Data analysis and map by the author. FY 2018 arrests are for the first eight months of the fiscal year.

Given that the data has an overdispersion of zero observations (counties with no noncustodial arrests) the best way to predict the output is through a Zero-Inflated Poisson (ZIP). A traditional Poisson regression is a maximum likelihood model for predicting count outputs. However, a ZIP is ideal for predicting dependent variable counts with excessive zeros. The concept behind the ZIP, as explained by Hilbe (2014, 198–99), is that there is a distinction between good and bad zeros. While some cases may legitimately produce a zero output, the ZIP model assumes there are some cases where a zero is the only possible outcome, hence there are excessive zeros. Think, for example, of a model that predicts the number of doctor visits individuals make in a month. Some
individuals may never visit the doctor (zero outcome), not because they were not sick but because they lack health insurance. Thus, there are excess of zero outputs.

For this study, it could be argued that many of the zeros are the result of a county lacking immigrants or at least lacking enough immigrants for ICE to invest resources in the community, either through partnerships via IMAGE or other means of making noncustodial arrests. The ZIP model divides the number of noncustodial arrests into two possible predictions: one that predicts only zero outputs, and another that predicts a count distribution, the latter of which could be a zero (Hilbe 2014). In other words, the ZIP assumes that some counties in the dataset will always produce zero noncustodial arrests, while others may produce zero arrests, but they at least have a positive probability of having one or more noncustodial arrests.

Table 2 displays the results of the ZIP models predicting noncustodial arrest rates for the two years of data. For the count models of interest (those not predicting excessive zeros), the incidence rate ratios (IRRs) are presented in substitution of the coefficient. The IRR can be interpreted as the increased likelihood of the event happening (a custodial arrest), resulting from an increase in the independent variable. The IRR is always positive, with values below 1 denoting a negative relationship. Immediately obvious is the positive relationship with IMAGE agreements. While the IRR of IMAGE agreements is relatively small, it is highly statistically significant for both the FY 2017 and 2018 models. For every additional IMAGE MOA in the county, the number of noncustodial arrests increased by a factor of 1.06 in FY 2017 and 1.05 in FY 2018, holding the other variables constant. In other words, with each additional agreement, the likelihood of arrest increased by 6% in 2017 and 5% in 2018. The relationship between IMAGE agreements and predictions as to whether a county would be in the inflated zero category (would never produce an arrest) is insignificant.

Table 2. ZIP Models Predicting Noncustodial Arrests

<table>
<thead>
<tr>
<th>Variable</th>
<th>FY 2017</th>
<th>FY 2018</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>Inflated (0s)</td>
</tr>
<tr>
<td>IMAGE MOAs</td>
<td>1.06***</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>287(g) MOAs</td>
<td>0.94</td>
<td>-1.39</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>IGSA Capacity per 100</td>
<td>1.12***</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Anti-detainer Policy</td>
<td>1.18***</td>
<td>-0.21</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>ISO Index</td>
<td>1.02</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.97***</td>
<td>-0.01*</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>% Hispanic Change</td>
<td>0.98*</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>1.05***</td>
<td>0.15**</td>
</tr>
</tbody>
</table>

18
Table 2. ZIP Models Predicting Noncustodial Arrests

<table>
<thead>
<tr>
<th>Variable</th>
<th>FY 2017</th>
<th>FY 2018</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count (0.01)</td>
<td>Inflated (0s) (0.05)</td>
</tr>
<tr>
<td>Gini Coefficient</td>
<td>2.89*** (0.09)</td>
<td>2.68*** (0.01)</td>
</tr>
<tr>
<td>% Republican Vote</td>
<td>0.97*** (0.00)</td>
<td>0.97*** (0.00)</td>
</tr>
<tr>
<td>Crime Rate</td>
<td>0.99*** (0.00)</td>
<td>0.99*** (0.00)</td>
</tr>
<tr>
<td>Border 100 Miles</td>
<td>3.34*** (0.15)</td>
<td>3.11*** (0.17)</td>
</tr>
<tr>
<td>Population per 50,000</td>
<td>0.98*** (0.00)</td>
<td>0.99*** (0.00)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.07 (0.17)</td>
<td>0.74 (0.15)</td>
</tr>
<tr>
<td>Vuong (Zip vs. Poisson)</td>
<td></td>
<td>7.24***</td>
</tr>
<tr>
<td>LR chi²</td>
<td>20,477.14***</td>
<td>10,966.90***</td>
</tr>
<tr>
<td>Nonzero Cases</td>
<td>354</td>
<td>281</td>
</tr>
<tr>
<td>Zero Cases</td>
<td>2,165</td>
<td>2,238</td>
</tr>
<tr>
<td>N</td>
<td>2,519</td>
<td>2,519</td>
</tr>
</tbody>
</table>

Dependent variable is number of noncustodial arrests in the county for FY 2017 and first eight months of FY 2018. Count model cells display the incident rate ratios (IRRs), unstandardized coefficients with standard errors in parentheses. IRRs below 1 indicate a negative relationship.

*p < 0.05; **p < 0.01; ***p < 0.001

The three ICE cooperation variables are listed immediately under the IMAGE MOAs. Two of the three are significant and behave according to a priori prediction. Each increase in the IGSA facilities capacity to hold immigrants (by 100) corresponds to a significant 12% and 2% increase in the likelihood of a noncustodial arrests in FY 2017 and FY 2018, respectively. Communities with anti-detainer policies, also experienced a significant increase in the likelihood of a noncustodial arrest, 18% more likely (FY 2017) and 23% more likely (FY 2018). The 287(g) variable was not significant. In fact, the effect was negative and was surprisingly close to significant in the FY 2017 model.21

Some of the county demographic (control) variables are also significant. Whether the county was located within 100 miles of the Mexico border had the largest effect. Counties on or close to the border were three times more likely to produce noncustodial arrests in both years. The outputs also lend some support to the conflict theory and economic-hardship explanations of immigration enforcement, i.e., that communities with economic adversity more aggressively enforce immigration policies. The unemployment and Gini coefficient variables are both significant. Notably,

21 p = 0.055.
a one-unit increase in the Gini coefficient (inequality within the county), corresponded to an increased likelihood of arrests by nearly three times in FY 2017 and more than two and a half times in FY 2018.\textsuperscript{22}

**Discussion**

PPPs are abundant in modern governments. However, IMAGE is unlike most traditional PPPs. By incorporating private employers into the business of immigration enforcement, private actors are partaking in a policy that is inherently punitive. There are serious implications associated with such a program. This study primarily sought to demonstrate whether local participation in IMAGE increased ICE’s direct local enforcement actions, specifically noncustodial arrests. Based on the models in Table 2, it appears that local participation in IMAGE is a significant factor in explaining local noncustodial arrests, supporting Hypothesis 1. The likelihood of noncustodial arrests significantly increased in both FY 2017 and 2018 with increased participation in IMAGE by local employers.

ICE relies on cooperation from other entities to enforce immigration policy. Case in point, the capacity of ICE to hold immigrants in detention (IGSA capacity per 100) significantly increased the likelihood of noncustodial arrests in both models. Additionally, the effect of having an anti-detainer policy in the county also increased the likelihood of ICE noncustodial arrests in both models, which was anticipated. These findings support Hypotheses 3 and 4. The latter also suggests that ICE made good on threats to increase enforcement in communities that chose to adopt sanctuary policies (ICE 2020). Trump signed his executive order directing ICE to target sanctuary communities in late January 2017. This data supports the theory that ICE sought to ramp-up direct enforcement in sanctuary communities where local government has limited law enforcement from participating in S-Comm.

However, participation in 287(g) yielded unanticipated results. Communities with 287(g) MOAs experienced a lower likelihood of noncustodial arrests, albeit insignificantly. The 287(g) program deputizes local law enforcement agents to assist with enforcing immigration statutes, which are civil law. ICE may be focusing its enforcement actions on communities where it lacks partner agencies to make immigration arrests. Whatever the explanation, Hypothesis 2 should be rejected.

The % Republican vote was significant for predicting arrests in both models. Based on the analysis here, it certainly appears ICE is focusing its noncustodial arrests in more liberal communities. Because liberal progressive communities are more likely to adopt anti-detainer policies, future research should explore the interaction between local political ideology and the adoption of anti-detainer policies on ICE noncustodial arrest rates. Among the demographic and control variables, increases in nonprofit services for immigrants does not correspond to lower likelihoods of arrests and, in the FY 2018 model, ISO services actually significantly increased the likelihood of arrests. The findings here could simply confirm that ISOs are concentrating in areas where immigrants are already facing proliferation of arrests and removals.

Finally, the analysis also confirms the repeated findings of prior studies that have noted ICE’s enforcement actions have little if anything to do with local crime rates. If ICE was using direct

\textsuperscript{22} The Vuong statistic, presented for both models, tests whether a zero-inflated model is appropriate vs. a traditional count model. The test is statistically significant for both models, indicating that the ZIP is the appropriate analysis over a traditional count.
enforcement actions for the genuine purpose of fighting crime, we would see a significant—and positive—relationship between the local crime rate and noncustodial arrests. We see no such effect. In fact, the county crime rate corresponded to a significantly lower likelihood of ICE noncustodial arrests in FY 2017, albeit the effect was small (1%).

As with all studies, there are limitations to acknowledge regarding these findings. First, it is important to stress that this study only demonstrates an associative, not causal, relationship between IMAGE and noncustodial arrests. More data is needed to confidently determine whether IMAGE agreements are the actual cause of noncustodial arrests increasing. For example, this study contains no local estimates on the number of undocumented immigrants at the county level because such estimates do not exist (at least to the author’s knowledge). It is likely that businesses are more inclined to enter into IMAGE agreements in communities with high percentages of undocumented immigrants, and the percent of undocumented immigrants itself is highly likely to be related to noncustodial arrests. Furthermore, information about IMAGE itself is incomplete. Specifically, future studies would benefit from more information on when IMAGE agreements with ICE became active. This would allow for time-series analysis in addition to the cross-sectional models used here. Unfortunately, despite repeated FOIA requests, ICE has not been forthcoming with the dates the agreements were signed.

Some may question what the policy implications for this study are. Specifically, what should be done to a program like IMAGE? The data shows that the IMAGE program enables ICE’s enforcement capabilities. There is a statistically significant positive relationship between the number of MOAs in a county and the number of direct, noncustodial arrests by ICE. However, in this author’s view, IMAGE’s ethical implications, discussed throughout this paper, far outweigh its potential benefit. As the institution with the “monopoly on the legitimate use of violence” (as Max Weber famously noted), the responsibility for detaining and deporting individuals should remain under government (i.e., state) control. These institutions, though not perfect enforcement vehicles either, are run or overseen by elected policymakers that must answer to public scrutiny. They have controls in place to protect private information, and they have the authority to act on behalf of the US government, even when those actions are harmful to the target community (detention and deportation).

Private businesses do not have the public oversight, privacy controls, or authority of government institutions. Businesses respond mostly to the incentive of making money, and mixing profit seeking motivations with immigration enforcement responsibilities is problematic at best. This is not to say there is no role for the private sector in immigration policy. Every government agency to some extent contracts with private businesses. In recent years, DHS has contracted with a range of large tech companies such as Microsoft, Motorola, Hewlett-Packard, and Dell to enhance its capacity to enforce immigration policy (Brandom 2018; Molla 2019). While critics would note that these contracts come with their own ethical issues, these are private contracts with government—not traditional PPPs. When Microsoft sells software to ICE, it is providing a product to an agency that ultimately exercises authority over how to use it. In such an arrangement, Microsoft is no more responsible for the discretionary decisions involved with enforcing immigration policy than the retail outlet that sold ICE office equipment. Furthermore, some may argue that large corporations such as Microsoft are less likely to be muscled into policy decisions than the many small and local employers who participate in IMAGE. For example, Apple famously refused to comply with the FBI’s demands to make the company’s iPhones easier to hack (Grossman 2016).
This is the first examination of IMAGE. The ethical implications of this program and the harsh punishments enforced on individuals ensnared in it should be enough to merit a level of scrutiny IMAGE has yet to receive.
References


