The Political Economy of Immigration Enforcement: Conflict and Cooperation under Federalism*

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Abstract

We study how local and federal responsibilities shape immigration enforcement outcomes. Tracking the movement of unlawfully present immigrants along the deportation pipeline, we propose a framework to decompose the variation in deportation rates between federal and local enforcement efforts, and the composition of the pool of arrestees. We estimate that among urban counties, 80% exhibit strategic substitutabilities in their response to changes in federal enforcement intensity, and that the federal level is very effective at directing its efforts toward counties where it expects local collaboration. We use the model estimates to quantify the impact of a 2011 shift in federal enforcement priorities on the number and composition of deportations, showing that a large fraction of the heterogeneity in outcomes can be attributed to different local responses. Finally, reducing the discretion of the immigration courts and removing their dependence from the executive power would have a significant impact on deportations.

Keywords: Immigration enforcement, Secure Communities, federalism, law enforcement, crime.

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1 Introduction

A long tradition in the social sciences has studied the allocation of tasks across different levels of government in the context of federalism (Hooghe and Marks (2003); Inman and Rubinfeld (1997b); Oates (1999)). Scholars have emphasized that the extent of decentralization should be driven by the degree of preference heterogeneity and the salience of local information, because the social value of locally tailored policies must be traded-off against the benefits of coordination or scale economies in public goods provision (Tullock (1969)). The existence of such trade-offs suggests we should observe more decentralization and more conflict where there is more preference heterogeneity (Besley and Coate (2003); Strumpf and Oberholzer-Gee (2002)), and increased spatial sorting across jurisdictions where policy is more decentralized (Tiebout (1956)).

Other important aspects of federalism, however, have not received as much attention. In several policy dimensions, rather than allocating disjoint tasks to different levels of government, both the federal and the local levels undertake overlapping actions that jointly determine policy outcomes (either because it is difficult for the federal level to implement policy without local-level aid[1], or because the local level is able to exercise some discretion). Moreover, the local level is often not just an agent of the federal level. In the US this is established in the 9th and 10th Amendments to the Constitution, which allocate to the states and the people any rights not explicitly delegated to the federal government. In such circumstances, we may expect coordination to take place when local and federal preferences are aligned. Otherwise, the local level may partly or fully undo the actions of the federal level.[2] As such, variation in the extent of preference alignment between levels of government should be a major driver of policy-outcome heterogeneity across jurisdictions, and of the success or failure of the policies themselves.

In this paper we explore precisely this possibility by studying immigration enforcement policy in the US. Immigration enforcement is an ideal setting to study strategic interactions under federalism. Although from a legal standpoint immigration policy falls under the purview of the federal government[3], in practice many margins of its enforcement are directly and indirectly affected by local-level decisions. Demographics, partisanship, and proximity to borders all shape local preferences over immigration policy. As a result, there is ample variation in the extent of

[1] In Federalist No. 44, James Madison recognized that in many instances the federal government would be dependent upon state and local governments to cary out policy, which in his view justifies the Supremacy Clause of the Constitution (Madison (1788)). In the case of immigration enforcement which will concern us here, while the payroll of ICE in 2010 was approximately 20 thousand employees, the number of state and local law enforcement officers across the US was more than 800 thousand (Reaves (2010)).

[2] De Tocqueville raised this issue early on: "Among the weaknesses inherent in all federal systems, the most obvious of all is the complexity of the means it employs. This system necessarily brings two sovereignties into confrontation" ((DeTocqueville, 2003 [1840], p.192)).

[3] Under current law immigration violations are federal offenses. Current federal immigration law is regulated by the 1952 Immigration and Nationality Act, its 1965 amendments, the Immigration Reform and Control Act of 1986, the Personal Responsibility and Work Opportunity Reconciliation Act of 1996, the Illegal Immigration Reform and Immigration Responsibility Act of 1996, and the REAL ID Act of 2005.

alignment of preferences over its enforcement between the federal and the local (county) levels.

Strategic interactions between levels of government arise in many settings beyond immigration enforcement, such as school funding, tax enforcement, the administration of the foster care system, or environmental protection and regulation just to mention a few (see Cascio et al. (2013); Mann (2011); Rechtschaffen and Markell (2003)). A central challenge in any of these settings is to understand the nature of the strategic environment, and to distinguish the different margins of enforcement from each other and from the underlying economic environment shaping both policy choices and policy outcomes. Perhaps except for Agarwal et al. (2014); Bohn et al. (2015); Fredriksson and Mamun (2008); Knight (2002), there is scant empirical literature exploring these issues or highlighting how strategic responses across levels of government are key to understand heterogeneity in policy outcomes.

We consider the enforcement of immigration policy under the Obama administration during the period of operation of the Secure Communities program. Under this program, whose rollout began under the George W. Bush administration, the fingerprints of every person arrested by local police are automatically sent to the Department of Homeland Security's Immigration and Customs Enforcement agency (ICE), where they are automatically compared with a variety of law enforcement databases to establish the immigration status of the arrestee. This allows ICE to locate potential targets of deportation, without requiring the acquiescence of local law enforcement. ICE then has full discretion to issue or not a detainer request to the jail where the arrestee is being held. The detainer asks local law enforcement to hold the arrestee for up to an additional 48 hours, giving ICE time to take the arrestee into federal custody. At this point a deportation process may begin. Between 2009 and 2014 under the Secure Communities program, ICE issued 485 thousand detainers, held in custody 479 thousand people (with and without issued detainers), and removed 396 thousand individuals.

The period covered by the Obama administration is especially convenient for our purposes because midway into the eight-year term, the administration undertook a major shift in immigration enforcement policy at the federal level[4]. The new guidelines explicitly advocated a shift in the focus of federal enforcement efforts away from the prosecution of unlawfully present immigrants accused of misdemeanors and minor crimes, and towards those accused of serious crimes. Trends in aggregate federal immigration enforcement outcomes indeed show a sharp reversal following the policy change, allowing us to leverage this change in federal immigration enforcement intensity to trace the heterogeneous responses of the local level to it.

Our starting point is to propose a framework that exploits the institutional details of the pipeline taking unlawfully present immigrants arrested by local law enforcement into ICE custody, and subsequently into being deported.[5] The immigration enforcement process operates in a

[4]See the policy memoranda issued by ICE's director John Morton (Morton (2011a,b)).

[5]A parallel branch of federal immigration enforcement consists in the raiding of homes and workplaces by ICE. Because this branch of immigration enforcement does not involve the local level directly, we do not consider it here.

cascade fashion. After local law enforcement makes an arrest for any offense, government agents at the local and federal levels undertake efforts that may result in the arrestee's transfer to federal custody. At that stage, the federal level and immigration courts jointly undertake efforts that determine whether the arrestee is removed from the US. Thus, observed removal rates depend on local and federal enforcement efforts, on how these interact along the immigration enforcement pipeline, and on the underlying composition of the pool of arrested unlawfully present individuals (because their characteristics may make them more or less favored by the local and federal levels). The key empirical challenge, thus, is to disentangle the roles of local and federal immigration enforcement efforts on the one hand, and of the composition of the arrest pool on the other, as drivers of the observed variation, across time and jurisdictions, in the observed removal rates. This is particularly difficult because local and federal enforcement choices are endogenous to each other (e.g., if the county strategically responds to choices of the federal level), and are likely dependent on arrest pool characteristics.

The pipeline nature of the Secure Communities program allows us to isolate enforcement choices from selection (unobserved characteristics of the pool of arrested unlawfully present individuals), and to isolate local from federal enforcement decisions. The automatic receipt of fingerprints by ICE after a local arrest implies that local-level enforcement choices have no (direct) effect on the likelihood of a detainer request, allowing us to isolate federal enforcement efforts from this first step. After ICE has issued a detainer request, the local level has full discretion to comply with it (by holding the arrestee until ICE picks him up) or not (by releasing the arrestee before ICE shows up), allowing us to isolate the local enforcement efforts from this second step. Tracing how the composition of the pool of arrestees is filtered through the several steps of the immigration enforcement pipeline, we are also able to disentangle the variation in the composition of the pool of arrestees from the variation in these enforcement choices. Leveraging these institutional features allows us to avoid imposing assumptions about details of the underlying game being played between the federal and the local levels, such as specific utility functions, beliefs, or information sets. We consider this to be a methodological advantage of our approach. In fact, we begin with a fully non-parametric analysis under which we provide partial identification results. We then rely on mild parametric assumptions sufficient to point identify the parameters of interest and conduct the rest of the empirical analysis.

A similar framework could be applied to settings where there is a sequentially structured institution. Appeals processes on judicial courts, applications for social programs or mortgages, job promotions, bills moving between committee and floor in Congress, to mention a few, are all settings where players make choices sequentially that induce selection into subsequent stages.

For a discussion of the increasing use of ICE raids during the Bush administration, see Schmall (2009). During the Obama administration, however, ICE raids were a small component of all federal immigration enforcement activity: between 2009 and 2016, only 12 percent of removed individuals were in ICE custody as a result of a raid (our own estimate based on Freedom of Information Act requests to ICE).

Explicitly modeling these pipelines based on their institutional details can similarly allow distinguishing the patterns of selection from the choices of the players.

We use detailed information on the universe of fingerprint matches under Secure Communities, the issuance of ICE detainers, the number of individuals under ICE custody, and the number of removals covering the period 2009-2014. We complement these data with information on a variety of county-level demographics. We first show that federal immigration enforcement did weaken considerably after the policy change, but that it cannot fully account for the pattern of changes in immigration enforcement outcomes along the deportation pipeline. In particular, strong selection forces in the composition of the pool of individuals facing prospects for removal, possibly endogenous to the changes in enforcement, were present. We also show that the choices of the local level had screening effects explaining part of these selection patterns.

We then estimate our model of the immigration enforcement pipeline under Secure Communities, and find most counties exhibit strategic substitutabilities in their response to federal enforcement efforts. This is true for cases of individuals accused of both minor and serious crimes. We find that local responses, however, were heterogeneous: more democratic and less Hispanic counties were more eager to undo the federal enforcement efforts by weakening their collaboration with ICE. A 10-percentage-points higher democratic vote share is associated with 7 percent and 25 percent more negative slopes in the response of the average county to changes in federal enforcement efforts over minor and serious offenses cases. We also find that changes in the acuteness of conflict between local and federal levels was mostly driven by a change in the profile of immigration cases prioritized by ICE. While ICE did strengthen its enforcement efforts towards serious offenses cases following the guidelines change, which was partially undone by the local level response, even more important quantitatively was the concomitant change in ICE's priorities over the types of immigration cases it faced. Our results also uncover a remarkable targeting ability by ICE: under Secure Communities, the agency was able to direct its enforcement efforts towards counties where it could expect more local collaboration. We also subject our model to several specification tests, all delivering encouraging results.

The estimated model allows us to assess the impact of the 2011 ICE guidelines on federal and local preferences and on removals. After the change in guidelines, counties became, on average, less willing to deport Mexican nationals targeted by ICE and more willing to deport un-convicted unlawfully present immigrants. In contrast, the average county became less willing to remove those convicted for assaults and drug trafficking. We also undertake a counterfactual simulation supposing the federal enforcement guidelines were never modified, while holding the composition of the arrest pool constant. This allows us to assess how the policy affected the number and composition of removals. We estimate that the guidelines are responsible for a 15 percent drop in removals of minor offenses cases, and a 50 percent drop in removals of serious offenses cases. Around 60 percent of counties would have observed higher counterfactual deportations. Our results highlight how conflict over policy across vertical jurisdictional levels constitutes a first-order driver of policy-outcome heterogeneity. They also suggest that the implementation of enforcement technologies that become too effective may lead to reactive responses when there is conflict over the outcomes of such enforcement. Secure Communities is a case in point, as its effectiveness in detecting unlawfully present immigrants required a large countervailing response by localities opposed to harsh immigration enforcement, eventually leading to the official demise of the policy.

Finally, to gauge the importance of the immigration courts in shaping deportation outcomes, we undertake two counterfactual exercises. First, we simulate a scenario where immigration courts are not under the jurisdiction of the executive branch, holding the responses of local and federal levels constant. We find that independent immigration courts would increase the number of removals, particularly for serious offenses and mostly in the period after the guidelines were implemented. Second, we evaluate the importance of the discretionary component of removal decisions by the immigration courts simulating a scenario where their severity is homogenized conditional on county observables. Forcing all counties to be as lenient as the county at the 10th percentile of severity, aggregate removals would be 39 percent lower for minor offenses and 25 percent lower for serious offenses during the Secure Communities period. This suggests that immigration courts exercise more discretion over minor offenses cases and that policies aimed at reducing arbitrariness in courts decisions could have a significant impact on removals.

Our paper contributes to the economics literature studying the effects of policy changes and interventions. A first concern is related to the presence of spatial heterogeneity that may be correlated with the take-up or the intensity of the policy in question (see Lalive and Zweimuller (2004); Meyer (1995); Rosenzweig and Wolpin (1986)). Time-varying heterogeneity in the effects of policies is also a concern, even when using jurisdiction-level fixed effects (Besley and Case (2000)). In our context, the response of the local level to the federal level is a source of heterogeneity in both the intensity of enforcement, and the effects of the policy (strategic interactions between federal and local enforcement margins may be present). Studying an institutional environment with features of federalism and policy overlap across levels of government, we address these concerns by leveraging the details of the institutional setting.

Within the literature on federalism and decentralization (Inman and Rubinfeld (1997a); Lockwood (2002); Strumpf and Oberholzer-Gee (2002)) we point to the local-federal alignment in preferences as a key political economy consideration for understanding variation in policy choice and policy outcomes. To the best of our knowledge ours is the first study recovering the enforcement responses of the local level to changes in federal-level enforcement. We show that differences in immigration enforcement preferences over immigrants with different criminal offense accusations are an important driver of the conflict between the federal and the local levels.[6]

[6]Because all interior enforcement of immigration in the US relies on the contact of unlawfully present immigrants with law enforcement, our study is also related to the literature on the economics of crime and immigration. This literature has pointed out that toughened immigration enforcement drives immigrants towards illegal activities

We also contribute to the literature on the political economy of immigration policy and law enforcement.[7] Scholars have studied the correlates of local and state-level immigration legislation (Boushey and Luedtke (2011); Steil and Vasi (2014)). Their findings suggest that the presence of a large immigrant community and of Hispanics correlates strongly with the passage of ordinances weakening immigration enforcement. The ethnic identity of local law enforcement is also correlated with the willingness to enforce immigration policies (Lewis et al. (2013)). Republican support, in contrast, is correlated with the adoption of stronger immigration enforcement policies, particularly in communities experiencing fast growth of the immigrant population (Ramakrishnan and Gulasekaram (2013)). Using a regression discontinuity design, however, Thompson (2018) finds no evidence of differences in compliance with detainer requests between barely elected Democratic or Republican sheriffs. In contrast, we find that local responses undoing federal efforts are stronger in more Democratic counties, but weaker where the Hispanic population share is larger.

The remainder of this paper proceeds as follows. In section 2 we discuss immigration policy in the US, with a focus on the Secure Communities program. We describe the data in section 3. Based on our background discussion, section 4 develops a model of the immigration enforcement pipeline, and section 5 discusses identification and estimation. In section 6 we present our main results and discuss their implications. Finally section 7 concludes. We present proofs and additional tables, figures, and data description in the online appendices.

2 Immigration Policy under Secure Communities

Starting with the 1849 Supreme Court decisions in *Smith v. Turner* and *Norris v. Boston*, the so called Passenger Cases, immigration policy and its enforcement in the US was gradually centralized. There the court established that levying state taxes on ships of immigrant passengers violated Article 1 of the Constitution. The Immigration Act of 1882, the first national-level piece of immigration legislation in the US, then allocated all power in determining the excludability and deportability of aliens to the federal level. However, it also left most practical enforcement to state-level officials (Hirota (2013); Hutchinson (2016)). Congress passed an additional piece of legislation in 1891 that completed the nationalization of immigration enforcement. This law granted wide discretion to immigration officers regarding admission of immigrants, raising early concerns about due process that reemerged recently under the Secure Communities program.

States and localities only began regaining a significant role in immigration policy with the

(Freedman et al. (2018)). Looking specifically at Secure Communities, however, both Miles and Cox (2014) and Treyger et al. (2014) find no effects of the program on crime rates.

[7] A recent related literature studies how immigrants and their families alter their economic choices in response to increased immigration enforcement, for example in school attendance (Dee and Murphy (2018)), geographic mobility (Amuedo-Dorantes et al. (2013)), or social welfare program enrollment and take-up (Alsan and Yang (2018); Watson (2014)). Most of this literature suggests these behavioral responses are the result of "chilling effects", as immigrants perceive interaction with government officials more risky.

1986 and 1996 legislative overhauls of immigration law. Both acknowledged the potential for local involvement in immigration enforcement. The Immigration Reform and Control Act (IRCA) of 1986 legalized almost three million unlawfully present immigrants but introduced employment restrictions for new ones. It also created the *Criminal Alien Program* (CAP), still in operation. Under CAP, local officials in prisons, jails, and courthouses share lists of inmates and allow ICE to perform interviews, after which ICE may issue detainer requests.[8]. The Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) of 1996, in turn, allowed states and localities to participate in immigration enforcement. Section 287(g) of the law allowed for cooperation agreements with the federal government, whereby local law enforcement officials received training and authority to enforce federal immigration law.[9]

Beyond these agreements, several states made further attempts at direct immigration enforcement. In 1993 California passed legislation mandating cooperation between state prisons and federal immigration authorities. California voters then approved Proposition 187 in 1994, requiring that state officials report suspected unlawful presence to federal authorities (Gulasekaram and Ramakrishnan (2015)). This proposition was struck down by the courts, but it did trigger similar efforts in Arizona, Florida, and Texas.

2.1 The Secure Communities Program

Conflict over immigration policy has grown considerably in the 21st century, as local, state, and federal levels have all attempted to exert increasing influence over immigration enforcement. This may have been driven by the rising numbers of unlawfully present immigrants –from around 3 million in 1990 to about 12 million in 2008–, increased political polarization and partisanship, or the drastic changes in the structure of employment in the US economy.[10] Variation across space in local preferences over immigration policy has grown, leading to sharp contrasts and reversals in the alignment of preferences between the federal and local levels.

States like Arizona led the charge on anti-immigration legislation. This state's SB 1070 bill, passed in 2010, became a prominent piece of legislation empowering local law enforcement to participate in immigration enforcement. Colorado, Alabama, Georgia, and South Carolina undertook similar 'copycat' attempts (Gulasekaram and Ramakrishnan (2015)). On the opposite extreme, several cities and counties have approved "sanctuary" ordinances requiring their law

[8]Through CAP, ICE has presence in every state and federal prison, and in more than 300 local jails. Currently CAP accounts for around half of all individuals taken into ICE custody (Guttin (2010); Kalhan (2013))

[9]This included the authority to screen individuals for their immigration status, investigate cases, issue detainers, arrest and issue charges for immigration violations, and access DHS's databases. Approximately three percent of counties eventually entered into a 287(g) agreement, most of them after the 9/11 terrorist attacks. As of 2018, 78 such agreements are in place (see: `https://www.ice.gov/287g`).

[10]Using regression analysis for the US, both Gulasekaram and Ramakrishnan (2015) and Steil and Vasi (2014) find that the partisan share of the electorate is a robust predictor of local immigration legislation adoption in this period. Fasani (2009) finds in the Italian context that increases in labor demand led to significant falls in deportations of immigrants between 1994 and 2004 and suggests a political economy mechanism for this effect.

enforcement officials not to collaborate with federal officials, and to explicitly ignore immigration violations. Sanctuary legislation is not new -some cities passed similar ordinances in the 70s-90s-. In recent years, however, new forms of non-cooperation emerged, partly as a response to federal enforcement efforts under the Bush and Obama administrations.

Possibly the most prominent federal effort in immigration enforcement in this period is the Secure Communities program, the main focus of our attention in this paper.[11] The program oversaw the largest expansion of local immigration enforcement in U.S. history (Kalhan (2013)). Participation in Secure Communities is mandatory. Its rollout began in 2008, but the program was officially discontinued in November 2014 after significant controversy and local and state resistance.[12] However, the Priority Enforcement Program (PEP), a program in the same sprit and relying on the same institutional structure, replaced Secure Communities. Despite its demise, Secure Communities constituted a radical innovation, on both the institutional and the technological fronts. We now go on to describe how the program operated.[13]

2.1.1 First Step: The Federal Level

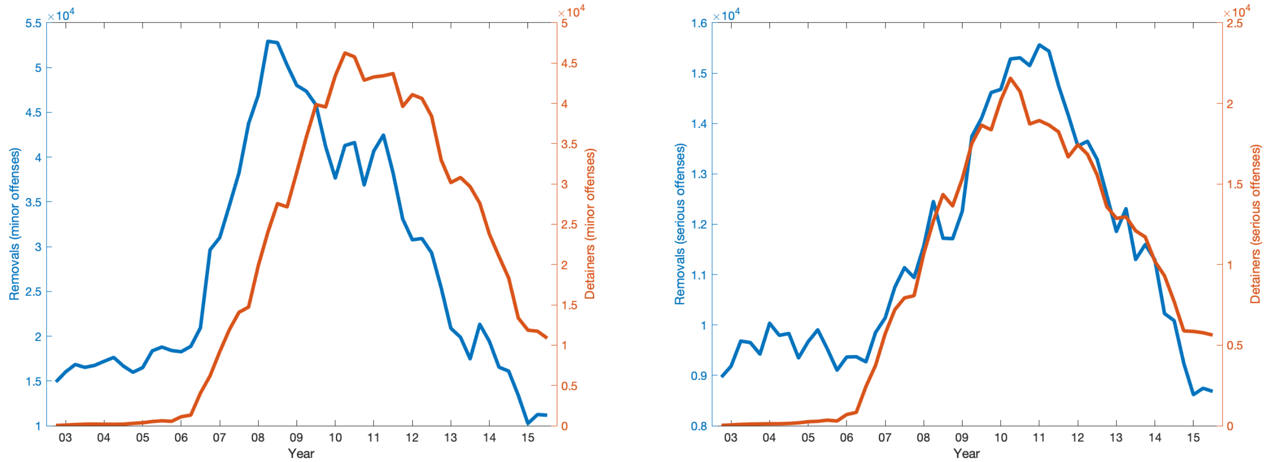
Secure Communities restricted significantly the ability of local police to exercise discretion over immigration enforcement. Under standard procedure following a local law enforcement arrest for any reason, the arrestee's fingerprints are scanned and checked against the FBI's identification and criminal records database (IAFIS) during booking. Under Secure Communities, upon receipt of these fingerprints, the FBI directly and automatically transmits them to the DHS for comparison against its Automated Biometric Identification System (IDENT)[14]. If there is a match to an

[11] ICE designed Secure Communities in response to a 2008 Congressional directive to "identify every criminal alien, at the prison, jail, or correctional institution in which they are held." (see *Consolidated Appropriations Act of 2008*).

[12] In the memorandum officially ending the Secure Communities program, the Secretary of Homeland Security Jeh Johnson argued that "The goal of Secure Communities was to more effectively identify and facilitate the removal of criminal aliens. But the reality is the program has attracted a great deal of criticism, is widely misunderstood, and is embroiled in litigation; its very name has become a symbol for general hostility toward the enforcement of our immigration laws. Governors, mayors, and state and local law enforcement officials around the country have increasingly refused to cooperate with the program, and many have issued executive orders or signed laws prohibiting such cooperation"(see Johnson (2014)).

[13] The Trump administration subsequently re-labeled PEP as Secure Communities.

[14] IDENT currently holds around 150 million records, and grows at around 10 million new entries per year. It contains information of any individual who has had contact with DHS, including visa applicants in other countries, non-citizens traveling through the US, non-citizens applying for asylum or other benefits, unlawfully present immigrants apprehended at the border, anyone participating in 'trusted traveler' programs, parents who have adopted children abroad, naturalized citizens, and anybody whose fingerprints have been collected through Secure Communities. It aggregates information from ICE, the Customs Border Protection, the US Coast Guard, the US Citizenship and Immigration Services, the Department of State, the Department of Defense, the Department of Justice (including all FBI databases), Interpol, the Five Country Conference (an information sharing agreement between the US, the UK, Australia, Canada and New Zealand), and the Preventing and Combating Serious Crime international agreement (see *Privacy Office, US Department of Homeland Security, Privacy Impact Assessment for the Automated Biometric Identification System (IDENT) 11–15 (2012), Office of Inspector General, US Department of Homeland Security, Operations of United States Immigration and Customs Enforcement's Se-*



(a) Minor offenses

(b) Serious offenses

Figure 1: Number of Detainers and Removals, 2003-2015. Figure (a) shows the aggregate number of detainers issued (red) and removals (blue) for arrestees charged with minor (levels 2 and 3) offenses. Figure (b) shows the aggregate number of detainers issued (red) and removals (blue) for arrestees charged with serious (level 1) offenses. Data are aggregated at the quarterly level. Source: TRAC.

unlawfully present individual, or even if there is no match but the individual has no known place of birth, the system automatically flags the record and notifies ICE. ICE itself then undertakes further checks on its own and other databases, and informs the corresponding ICE field office about any relevant findings.[15] The field office then decides whether to submit a detainer request to the local jail where the arrestee is being held. Thus, under Secure Communities immigration status verification became routine part of law enforcement. As a key first feature of the program, it eliminated all local-level discretion over immigration status verification: the local level can no longer affect the likelihood that the federal level learns about the immigration status of an arrestee.[16] This is in sharp contrast to the ample local discretion possible under CAP or 287(g).[17]

Once ICE officials have identified a person of interest being held at a local detention facility, they must decide whether or not to issue a detainer. Detainers are addressed to the local law enforcement agency, requesting to hold the arrestee in custody for up to an additional 48 hours. This gives ICE officers time to take the arrestee into custody. The detainer issuance decision is complex. ICE officials must evaluate all the information they have (and do not have) about the

cure Communities 4–5 (2012), and DHS, Privacy Impact Assessment for the Automated Biometric Identification System (2012)).

[15]ICE is organized geographically into 24 federal enforcement districts (see Figure B.2).

[16]Facing some challenges to this aspect of the policy (e.g., *Santos v. Frederick County Board of Commissioners* (2013), *Doe v. Immigration and Customs Enforcement* (2006)), DHS explicitly makes it clear that "a jurisdiction cannot choose to have the fingerprints it submits to the federal government processed only for criminal history checks" because "the sharing [of fingerprints] was ultimately between the FBI and DHS". (see Kalhan (2013).

[17]The only possibility here would be for the officers to not collect the fingerprints of an arrestee they believe may by illegally present in the country. This would constitute malpractice and would not allow the police to establish the criminal status of the individual in custody, making it impractical (Gulasekaram and Ramakrishnan (2015)). On the other hand, the arresting behavior of the police may have changed in response to the introduction of Secure Communities, which constitutes a first order source of selection which we will deal with below.

arrestee. This includes the severity of the offenses charged and any other prior criminal history, the individual's likelihood of being removed once under federal custody, and the availability of resources required to deploy a team that picks up the individual in the local detention facility. ICE officers follow a series of priority guidelines issued by ICE directors. They are also likely to have strategic considerations in mind: issuing a detainer request effectively 'alerts' the local level of the federal level's interest in the arrestee. If ICE officers deem the locality immigrant friendly, they may expect local law enforcement to expedite the release of the arrestee in response to the detainer. Federal discretion over the issuance of detainer requests is the second key feature of the institutional design of the program.

The main source of variation we exploit is the drastic change in the official priority guidelines for prosecutorial discretion undertaken by the Obama administration in the summer of 2011. The first two years of the Obama administration continued a trend of strengthened federal immigration enforcement, with increasing numbers of detainer requests and removals across the US.[18] Increased federal enforcement led to pressure from local governments and immigration advocacy groups, which, together with the forthcoming presidential election, were key factors explaining the policy change. Figure 1 plots the aggregate trends in the number of detainers and removals by offense severity (see below), showing the striking reversal around mid 2011. The new policy guidelines, outlined in a series of memos by ICE director John Morton, were predicated upon refocusing federal efforts and resources away from the prosecution of unlawfully present immigrants accused of minor offenses or just immigration violations, and towards those accused of serious crimes:

> "ICE must prioritize the use of its enforcement personnel, detention space, and removal assets to ensure... the agency's enforcement priorities, namely the promotion of national security, border security, public safety, and the integrity of the immigration system... Because the agency is confronted with more administrative violations than its resources can address, the agency must regularly exercise 'prosecutorial discretion',... the authority of an agency charged with enforcing the law to decide to what degree to enforce the law against a particular individual" (Morton (2011a)).

The memo goes on to specify which ICE officers are allowed to exercise discretion, and a long list of criteria for them to follow. Additional memos provided further instructions on the subject (Morton (2011b)). In practice, the Secure Communities program used a four-level classification for offenses. Level 1 being the most serious, includes convictions for homicide, kidnappings, sexual assault, and terrorist activity among others. Levels 2 and 3 include convictions for less serious crimes such as burglary, theft, traffic offenses, small drug offenses, and immigration violations (for the full list of categories of offenses, see ICE (2008)). Level 4 includes individuals that have not been yet convicted. The new guidelines redirected federal enforcement towards level 1 offenses. Our empirical strategy below will rely on this distinction.

[18] Compared to the pre-program period, Secure Communities saw a tenfold increase in the number of detainers issued by ICE (Kalhan (2013)).

2.1.2 Second Step: The Local Level

Local law enforcement is able to exercise discretion over immigration outcomes as well, but in the next stage of the process. Once ICE has submitted a detainer request, local law enforcement is free to decide whether to 'honor' it by holding the arrestee until pick up by ICE, or not to honor it by either releasing the arrestee before ICE shows up, or by refusing to hand over the immigrant to ICE. Indeed, detainer requests are not binding for the local level, and constitute only suggestions of collaboration.[19] Thus, the third key feature of Secure Communities is the complete discretion of the local level after a detainer has been issued.

This is also the stage at which the extent of preference alignment between the local and the federal levels is made manifest: because ICE moves first when deciding whether to issue a detainer or not, any arrestee for whom a detainer is issued is necessarily highly desired by the federal level, irrespective of ICE officers' beliefs about how the local level may react. This need not be the case for arrestees for whom ICE abstains from issuing a detainer; this set will include all arrestees ICE is uninterested in, and other arrestees which are of interest but for whom the agency did not issue a detainer based on strategic considerations. If the preferences of the local level are aligned with those of the federal level, local officials will be likely to honor the detainer request. Otherwise (i.e., the characteristics of the arrestee are such that the local level would rather not see this arrestee under ICE custody), we may expect the local officials not to honor the detainer. As a result, the rate of compliance with detainer requests will be informative about the extent of alignment of preferences between the local and federal levels.

Variation in local cooperation is partly driven by local preferences over the presence of unlawfully present immigrants. It also depends on the costs of compliance. First, holding arrestees for longer is expensive, and diverts resources from law enforcement. Moreover, localities also expressed concern about how participation in immigration enforcement would erode community trust. Indeed, conflict over Secure Communities grew rapidly as the federal government rolled it across the US. Several advocacy groups such as the National Day Laborers Network organized a resistance movement, focused on crafting legislation and lobbying local governments. In its non-cooperation ordinance, for example, the Cook county, IL council argued:

> "... it costs Cook county approximately $43,000 per day to hold individuals... pursuant to ICE detainers, and Cook county can no longer afford to expend taxpayer funds to incarcerate individuals who are otherwise entitled to their freedom... having the sheriff... participate in the enforcement of ICE detainers places a great strain on our communities by eroding the

[19] This has been established by several appeals and state supreme court rulings affirming the right of local level agencies to exercise discretion at this point under the anti-commandeering doctrine founded on the Tenth Amendment (See *Galarza v. Szalczyk* (2014), *Jimenez-Moreno et al. v. Napolitano et al.* (2014), *Buquer v. City of Indianapolis* (2011), or *Printz v. United States* (1997) among others). ICE officials themselves have acknowledged that detainers constitute only a collaboration suggestion. Moreover, some counties have argued that holding an arrestee who has not otherwise been charged with a crime, in response to a detainer request, may constitute a due process violation (Manuel (2012); Pham (2006)).

public trust the sheriff depends on to secure the accurate reporting of criminal activity..." (Cook county board of commissioners, Sept. 7, 2011)

Most of this legislation has the purpose of limiting the extent to which the local level collaborates in honoring ICE detainers. Some of the ordinances and regulations instruct local police to honor only detainers for arrestees charged with serious crimes. The best known example is California's TRUST Act, passed in 2013.

2.1.3 Third Step: ICE Custody and Removal

Arrestees in local detention facilities are taken into ICE custody in two ways. They may be picked up by ICE officers pursuant to a detainer request, which we refer to as the 'detainer track'. Or they may be picked up by ICE officers who show up to a local jail or prison unannounced in search for unlawfully present individuals. We refer to this as the 'direct track'. A key distinction between both tracks is that for arrestees with an issued detainer, the local level's detainer compliance decision fully determines the likelihood they are taken into ICE custody. For arrestees for whom no detainer was issued, both federal and local efforts shape the likelihood they are taken into ICE custody.[20] This distinction and availability of data from both tracks will be crucial for the identification strategy we lay down below.

In either case, individuals under ICE custody go on to a deportation proceeding involving immigration court. Under US law, immigration courts are *not* part of the judicial branch. Rather, they constitute a division within the Department of Justice, and thus, are part of the federal executive branch. As such, we may expect the outcomes at the removal stage to be correlated with the patterns of federal immigration enforcement earlier in the process, even though immigration courts are expected to apply the law uniformly and to respect due process and fair treatment. Unlawfully present individuals under ICE custody are free to waive their right to an immigration proceeding, in which case they are directly removed.[21]

3 Data Description

The Immigration Enforcement Pipeline. Our data on the immigration enforcement pipeline comes from two main sources. First, a series of Freedom of Information Act (FOIA) requests to DHS, from which we obtained information from the Secure Communities program at the county level, covering the universe of cases of unlawfully present individuals moving along the immigration enforcement pipeline between October 2008 and February 2015. These detailed data

[20]This will depend on the implicit or explicit negotiation between local and federal law enforcement at the time when ICE officers show up in a local detention facility.

[21]A host of legal aid organizations provide council to those who do not waive their right and are unable to hire private counsel. Although technically possible, the IIRIRA restricted considerably the possibility of appeals in the immigration court system, as it strips the federal courts of jurisdiction to hear legal challenges to deportation decisions (Zolberg (2006)).

include the number of fingerprint submissions from local detention facilities with matches to the DHS's IDENT database, the number of detainers issued by ICE, the number of individuals in ICE custody, the number of removals, and the ICE level of priority based on crime severity. For our purposes, we will consider level 1 as serious crimes, and levels 2 and above as minor crimes. We use the number of fingerprint matches as our measure of local arrests of unlawfully present individuals.[22] Second, we collected data from the *Transactional Records Access Clearinghouse* (TRAC) at Syracuse University. Based on several FOIA requests, TRAC has built updated record-by-record datasets of detainers, removals and Secure Communities removals with information from 2002 to the present. All datasets have information on the most serious crime conviction, priority level for ICE, country of birth, age, and sex of the immigrant. We combine these two sources and aggregate the data at the county-semester level, beginning with each county's enrollment in the program. We reconstruct measures by crime severity (serious and minor) of arrests of unlawfully present individuals, detainers issued by ICE, individuals in ICE custody with and without a detainer request, and removed individuals under ICE custody with and without a detainer request.[23]

Table B.1 presents descriptive statistics at the county-semester level for the several stages of the immigration enforcement pipeline. It reports counts of events, and divides the data between the pre and post policy guidelines change. The number of observations in the pre-guidelines regime is smaller than in the post-guidelines regime for two reasons: first, the pre period covers five semesters, while the post period covers seven semesters. Second, enrollment into the Secure Communities program, albeit mandatory for the counties, happened gradually as ICE rolled out the program starting in October 2008. By January 2013 all US counties were enrolled, and by the time of the policy change in June 2011, more than 70 percent of the US population was living in counties enrolled in the program (see Figure B.1 in Appendix B). Naturally, the timing of enrollment into Secure Communities is correlated with key county characteristics. Particularly predictive is the share of Hispanics (see Cox and Miles (2013)). Indeed, DHS possibly targeted counties for enrollment as a function of its own objectives, so entry into the sample is an important source of selection that may be reflected in these tables.[24]

Throughout this paper we restrict attention to counties with an estimated share of undocu-

[22]Naturally, false positives can arise when ICE flags a US citizen by mistake. Similarly, false negatives can arise when ICE fails to flag an unlawfully present immigrant. The former are likely to establish their citizenship later, and the latter will not be subject of ICE prosecution so these cases will introduce little error on our counts of detainers, custodies, and removals. On the other hand, fingerprints from an arrestee may be submitted multiple times. We have no reason to believe such occurrences may be related to immigration enforcement concerns, and were unable to identify any such cases from these data.

[23]The TRAC dataset allows us to assign the detainer requests to counties, and to establish whether a given removal followed a detainer request or not. Most importantly, this dataset allows us to assign ICE custody and removals cases to the detainer and the direct tracks (the data from DHS does not contain this information). We do the assignment by applying the TRAC-based shares of individuals under ICE custody or removed with detainers to the FOIA-based counts. Overall both sources agree, although we need to undertake some adjustments (described in Appendix C) in a subset of cases where inconsistencies arise.

[24]Neither Cox and Miles (2013) nor we find the county-level Democratic share to be predictive of Secure Communities activation after controlling for the Hispanic share.

mented immigrants above median (1 percent of the population), and thus, where there can be some federal-local conflict over immigration. Elsewhere immigration enforcement is not a locally salient issue, and we observe no variation in immigration outcomes.[25]

County Characteristics. We collected an array of county-level characteristics related to local preferences over immigration enforcement. We report summary statistics for these variables in Panel A of Table B.2. To capture political preferences, we focus on the Democratic share of votes from the 2008 and 2012 presidential elections, using David Leip's atlas of US presidential elections.[26] We also use other demographic characteristics taken from the American Community Survey 2006-2010 waves, as sources of variation in preferences over immigration enforcement: population, Hispanic share, share of adults with a bachelors degree, and share of employment in the services sector. Finally, Table B.2 reports summary statistics for whether the county is considered rural, the county's distance to its corresponding ICE district headquarters (see Figure B.2), and for the presence of 287(g) agreements (see Mayda (2006), for a discussion of the correlates of preferences over immigration policy).

3.1 Patterns of Immigration Enforcement Outcomes

We now present descriptive results illustrating the main changes in the patterns of immigration enforcement outcomes at each step along the immigration enforcement pipeline following the 2011 guidelines. Together, these results motivate our subsequent empirical strategy and modeling approach. To do this in a flexible way, we focus on measuring the average slope of the relationship between the outcome of a given step along the pipeline, y_{ct}, and its corresponding baseline, B_{ct}. For example, in the first step of the detainer track, we are interested in how many detainer requests are issued per unlawfully present immigrant in police custody. Estimating a fixed effects model, we recover the average rate at which baseline events translate into outcome events, and any differences in this rate between the pre and post-policy guidelines periods:

$$y_{ct} = \alpha_c + \tilde{\alpha}_t + \beta B_{ct} + \gamma(B_{ct} \times \text{Guidelines}_t) + \mathbf{x}'_{ct}\boldsymbol{\eta} + \epsilon_{ct} \tag{1}$$

[25] We construct a measure of the undocumented share using: the share of Hispanic non-citizens from the 2010 census, the number of tax returns filed without a social security number from Brookings (see https://www.brookings.edu/interactives/earned-income-tax-credit-eitc-interactive-and-resources/), and state-level estimates of unlawfully present population from Warren and Warren (2012). See Appendix C for a detailed explanation.

[26] See www.uselectionatlas.org. Besides the well established county-level correlations between local immigration enforcement regulations and Republican vote share, this relationship holds as well at the individual level: the 2015 American Trends Panel survey from the Pew Research Center, for example, found 71 percent of Republican voters believe that immigrants in the US make crime worse, compared to 34 percent of Democratic voters. See http://www.pewresearch.org/fact-tank/2015/09/30/on-views-of-immigrants-americans-largely-split-along-party-lines/.

where y_{ct} is an immigration enforcement outcome (detainers, ICE custodies, removals), B_{ct} is its corresponding baseline variable along the pipeline (arrests in the case of detainers, detainers in the case of ICE custodies, ICE custodies in the case of removals) and $\mathbf{x}_{ct}$ is a vector of controls.[27] Periods when the baseline variable is zero do not contain information on the enforcement rate, so the estimating samples only include observations for which $B_{ct} > 0$.

We estimate γ for the different steps of the deportation process. We use a standard inverse hyperbolic sine transform over the y_{ct} and B_{ct} counts, so the coefficients can be interpreted approximately as elasticities. Notice, however, that these coefficients do not have a causal interpretation: they will reflect equilibrium changes in enforcement by federal and/or local levels in response to the change in the guidelines, as well as equilibrium changes in the composition of the pool of baseline cases along dimensions relevant for enforcement decisions. This heterogeneity represents characteristics of the arrestees over which the local and federal levels have conflicting preferences regarding deportation. The pool of arrestees can change endogenously for several reasons. First, secular demographic patterns, such as the steady growth of the Central American migrant population in this period, can impact the composition of the pool of arrestees. Second, keeping constant the composition of the pool of immigrants arrested, federal and local preferences over the deportability of different types of immigrants may change. For example, under the 2011 guidelines ICE prioritized for removal immigrants without American-born children. Third, immigration enforcement itself can alter the composition of the pool of arrestees: it can undermine community collaboration with law enforcement relevant for efficient policing, and it can shift the supply of crime through both deterrence and incapacitation.[28] Moreover, each step of the immigration enforcement pipeline will generate selection in the downstream steps. This is especially clear when, for example, changes in the arrests-to-detainers stage lead to zero detainers, so that we no longer have information about enforcement rates in the detainers-to-custodies stage.

Minor Offenses. Along the detainer track, column 1 in panel A of Table 1 shows a significant coefficient on the interaction term: in the post-guidelines period, the rate at which arrests for minor offenses translate into detainer requests for the average county falls by more than 10 percent (-0.066 (s.e = 0.017) relative to a baseline of 0.614 (s.e. = 0.028)). This quantitatively large fall suggests that ICE did comply with the policy guidelines, by weakening enforcement towards minor crimes through the channel of reduced numbers of detainer requests. In the post-guidelines

[27] $\mathbf{x}_{ct}$ includes log population, and interactions between semester dummies and each of the following time-invariant characteristics: state dummies, ICE federal district dummies, undocumented share of the population, Hispanic share of the population, Democratic party share of the presidential vote, share of the population with a bachelors degree, a dummy for rural counties, and log distance to the corresponding ICE district headquarters.

[28] For example, suppose the guidelines led to weakened local immigration enforcement, and that this improves policing efficiency, leading to higher apprehension rates for minor offenses. The pool of arrestees will become selected towards these kinds of offenses, which are on average less likely to be requested by ICE. Thus, in the regression of detainers on arrests, γ will be negative partly as a result of weakened enforcement, and partly because the pool of arrestees endogenously shifted toward people over which ICE has little interest.

Panel A:	Detainer Track							
	Minor offenses				Serious offenses			
	(1) Detainers	(2) Custodies	(3) Removals	(4) Removals	(5) Detainers	(6) Custodies	(7) Removals	(8) Removals
Arrests	0.614			0.187	0.275			0.005
	(0.028)			(0.025)	(0.031)			(0.024)
Arrests × Guidelines	-0.066			0.001	0.029			0.102
	(0.017)			(0.022)	(0.022)			(0.020)
Detainers		0.648				0.637		
		(0.030)				(0.036)		
Detainers × Guidelines		-0.046				-0.056		
		(0.025)				(0.031)		
Custodies			0.579				0.287	
			(0.041)				(0.046)	
Custodies × Guidelines			0.009				0.136	
			(0.038)				(0.039)	
Observations	11269	8243	6294	11269	9656	5433	4010	9656
Adjusted R^2	0.90	0.84	0.84	0.80	0.86	0.83	0.82	0.81

Panel B:	Direct Track			
	Minor offenses		Serious offenses	
	(1) Custodies	(2) Removals	(3) Custodies	(4) Removals
Arrests (no detainer)	0.391	0.297	0.325	0.163
	(0.027)	(0.032)	(0.033)	(0.036)
Arrests (no detainer)×Guidelines	-0.088	-0.028	-0.053	0.052
	(0.020)	(0.024)	(0.025)	(0.028)
Observations	10476	10476	8797	8797
Adjusted R^2	0.88	0.87	0.85	0.85

Table 1: County Fixed Effects Models for the Steps of the Immigration Enforcement Process The table shows regression coefficients for panel fixed effects models for the different steps of the immigration enforcement process by type of arrest according to ICE's classification. All models include county fixed effects, semester fixed effects, log population, and interactions of semester fixed effects with the following time-invariant covariates: state dummies, federal enforcement district dummies, undocumented share of the population, Hispanic share of the population, Democratic party share, share of the population with a bachelors degree, a dummy for rural counties, and log distance to the corresponding ICE district office. Panel A presents results for the detainer track, while Panel B presents results for the direct track. Arrests correspond to the number of fingerprint matches under Secure Communities. Custodies and Removals in Panel A correspond to those for which a detainer was issued. Custodies and Removals in Panel B correspond to those for which no detainer was issued. Guidelines is a dummy variable indicating the semesters after the policy guidelines change under the Obama administration. All models exclude observations for which the baseline regressor is zero. Standard errors are robust to arbitrary heteroskedasticity, and clustered at the county level.

period, detainers also translate into ICE custodies at a smaller rate on average (-0.046, s.e $= 0.025$ relative to a baseline of 0.64, s.e $= 0.03$), although this difference is significant at the ten percent level only. This fall may be masking heterogeneous responses to the federal enforcement change, across counties with different preferences. It may also be driven by a significant change in the pool of unlawfully present individuals: although these are people detained for minor offenses, the federal level may already have screened out the least severe of these offenses when reducing the issuance of detainers.

Column 3 then moves towards the last step of the pipeline, where immigration courts with perhaps some influence by ICE determine the rate at which individuals in ICE custody are removed. This rate is no different between the pre and the post-guidelines periods. On the one hand, the immigration courts may have weakened their enforcement standards as well. On the other, the pool reaching an immigration court proceeding in the post-guidelines period may be composed of individuals with characteristics more favorable to deportation. As a complement to these results, column 4 reports the compounded effects implied by the full detainer track, looking at changes in the rate at which arrests of unlawfully present immigrants translate into final removals. Removals per arrest are indistinguishable between pre and post-guideline change periods for the average county. Considering how quantitatively large the federal policy change was, this suggests strong selection forces at play over the pool of people being taken through the immigration enforcement pipeline. Indeed, significant differences in the rates at which unlawfully present immigrants move along the first two steps of the pipeline following the change in guidelines can only be consistent with no differences in the net rate of removals if a large change in the composition of the pool of arrestees took place simultaneously.

Columns 1 and 2 in panel B report analogous results for the direct track, still among minor offenses cases. Along this track, the post-guidelines change period also saw a large and precisely estimated fall in the rate at which arrests translate into ICE custodies (-0.09, s.e.$= 0.02$). This fall is proportionally larger than the one observed along the detainer track.

Serious Offenses. In columns 5-8 of panel A we present the main patterns on immigration cases tagged as serious offenses. The 2011 policy guidelines advocated a shift towards immigration enforcement of serious offenses cases. Column 5 reports a statistically insignificant coefficient on the differential rate at which local arrests translate into ICE detainer requests (0.029, s.e.$= 0.022$). The fall in the raw numbers of detainers issued by ICE illustrated in Figure 1 above makes this finding particularly striking. It suggests a large change in the composition of this pool.

In the post-guidelines period detainers translate into ICE custodies at a lower rates (see column 6). In contrast, we observe a large post-guidelines increase of around 50 percent in the conditional removal rate at the ICE custody stage (in column 7, the interaction term is 0.136, s.e.$= 0.039$ compared to a baseline coefficient of 0.287, s.e.$= 0.046$). A similarly large change at the ICE custody stage can be seen along the direct track. In column 3 of panel B we show that along this track, on average each arrest led to less ICE custodies after the guidelines were issued, but to more removals in the post-guidelines period. Part of this pattern may be driven by a strongly selected pool of arrestees with characteristics highly amenable to deportation, and part by increased enforcement across the board at the immigration court stage.

A comparison between the detainer and no detainer tracks for serious offenses also suggests an enforcement response from the local level. If federal enforcement behaved similarly along both tracks, then the lower rates at which detainers and arrests translate into ICE custodies suggest a resistance response by the local level to the shift in enforcement towards serious crimes. Moreover, the local level may have resisted the removal of the least serious among these cases. This has a screening effect, selecting the pool of those who reach the immigration court stage towards individuals the immigration courts are eager to remove. To distinguish between these different margins, below we directly model the immigration enforcement pipeline.

4 A Model of the Immigration Enforcement Pipeline

We now present a framework to disentangle the three key sources of variation in the patterns of immigration enforcement we described in section 3: local and federal enforcement, and selection in the composition of the pool of unlawfully present immigrants moving along the pipeline. It will allow us to track how arrested individuals are filtered along this pipeline, and to capture the key features we highlighted above as critical for our empirical strategy. Most importantly, by incorporating time-varying unobserved heterogeneity in the composition of the pool of arrested unlawfully present individuals, we capture any misalignment of preferences over removals between the federal and local levels. Our knowledge of the institutional details of the enforcement process allows us to abstain from taking stances over utility functions, beliefs, or other details of the implicit game between both levels, and to remain almost fully non-parametric. Besides relying on the structure provided by the pipeline, we only rely on two substantial and readily interpretable assumptions made explicit below. Because the 2011 change in policy guidelines explicitly proposed directing federal enforcement efforts towards serious offenses cases, we condition the analysis on the (observed to us) crime severity, effectively allowing both the federal and the local levels to choose different intensities of immigration enforcement towards serious and minor offenses.

4.1 The Immigration Enforcement Process

Arrested unlawfully present immigrants vary in observed and unobserved (to us) characteristics. Conditional on their observed characteristics, most prominently the seriousness of the offense for which they were arrested, the local and federal levels may disagree on whether the individual should be a high or low removal priority. Because the relevant conflict between local and federal levels revolves around removal, the table at the top of Figure 2 describes the distribution of the

Pool of Arrestees

Local \ Federal	L	H
ℓ	$\pi^{L\ell}$	$\pi^{H\ell}$
h	π^{Lh}	π^{Hh}

Pool of Detainers

Local \ Federal	H
ℓ	$\pi^{H\ell} \,/\, (\pi^{H\ell} + \pi^{Hh})$
h	$\pi^{Hh} \,/\, (\pi^{H\ell} + \pi^{Hh})$

Pool of ICE Custodies

Local \ Federal	H
ℓ	$g\pi^{H\ell} \,/\, (g\pi^{H\ell} + \pi^{Hh})$
h	$\pi^{Hh} \,/\, (g\pi^{H\ell} + \pi^{Hh})$

Pool of Removals

Local \ Federal	H
ℓ	$q^{\ell}g\pi^{H\ell} \,/\, (q^{\ell}g\pi^{H\ell} + q^{h}\pi^{Hh})$
h	$q^{h}\pi^{Hh} \,/\, (q^{\ell}g\pi^{H\ell} + q^{h}\pi^{Hh})$

Pool of No Detainers

Local \ Federal	L	H
ℓ	$\frac{\pi^{L\ell}}{1-(\pi^{Hh}+\pi^{H\ell})f}$	$\frac{(1-f)\pi^{H\ell}}{1-(\pi^{Hh}+\pi^{H\ell})f}$
h	$\frac{\pi^{Lh}}{1-(\pi^{Hh}+\pi^{H\ell})f}$	$\frac{(1-f)\pi^{Hh}}{1-(\pi^{Hh}+\pi^{H\ell})f}$

Pool of ICE Custodies

Local \ Federal	H
ℓ	$k\pi^{H\ell} \,/\, (k\pi^{H\ell} + \pi^{Hh})$
h	$\pi^{Hh} \,/\, (k\pi^{H\ell} + \pi^{Hh})$

Pool of Removals

Local \ Federal	H
ℓ	$q^{\ell}k\pi^{H\ell} \,/\, (q^{\ell}k\pi^{H\ell} + q^{h}\pi^{Hh})$
h	$q^{h}\pi^{Hh} \,/\, (q^{\ell}k\pi^{H\ell} + q^{h}\pi^{Hh})$

Figure 2: The Immigration Enforcement Pipeline. The figure shows a flow chart of the immigration enforcement pipeline together with the distribution of unobserved heterogeneity along the process. The detainer track is in the left side, and the direct track is on the right side of the chart. L and H represent low and high priority arrestees for ICE. ℓ and h represent low and high priority arrestees for the local level. The π's represent the shares of each type in the population of arrestees. f is the probability of detainer issuance by the federal level, g is the probability ICE custody following a detainer, k is the probability of ICE custody in the absence of detainer, and q^{ℓ}, q^{h} are the probabilities of removal from the US for individuals in ICE custody of types $H\ell$ and Hh.

relevant unobserved heterogeneity in the pool of arrestees in a given county and time period.[29] $\pi^{L\ell}$ is the fraction of arrestees who are low priority for ICE (L) and low priority for the county (ℓ), while π^{Hh} is the fraction of arrestees who are high priority for both ICE (H) and the county (h). The higher these fractions, the more aligned the preferences of both levels. In contrast, π^{Lh} is the fraction of arrestees ICE is not interested in removing (L), but the local level would prefer were removed (h). $\pi^{H\ell}$ is the fraction of arrestees ICE would like to remove (H), but the local level would not want to see removed (ℓ). The higher these fractions, the more misaligned the preferences of the federal and the local level. Our knowledge of the immigration enforcement pipeline and its two "tracks" will allows us to trace how the pool of arrestees is filtered along the process, and to separately recover federal and local immigration enforcement efforts.

[29] All variables refer to a given county-time period (c, t). We omit those indices in this subsection as it does not lead to any confusion.

4.1.1 The Detainer Track

Along the first track, the ICE district office is automatically informed about the arrest of an unlawfully present individual, and decides whether to issue a detainer. Detainers are not issued for type L arrestees: $\mathbb{P}(\text{Detainer}|L) = 0$[30]. For type H arrestees, ICE issues a detainer with a probability that depends on the current intensity of federal immigration enforcement: $\mathbb{P}(\text{Detainer}|H) \equiv f$. Conditional on observed characteristics, this probability is constant within time periods (in our baseline empirical application, this will correspond to semesters). The 2011 guidelines, for example, directly changed f.

Assumption 1. *ICE does not condition on the local level preference type* $\{h, \ell\}$.

This is a weak assumption. First, recall it is conditional on the seriousness of the alleged offense. Moreover, from the point of view of ICE, all H types are on average equally desirable irrespective of their local type, h or ℓ. $\{h, \ell\}$ are residual characteristics of the arrestee directly relevant for the local level only. Part may represent characteristics of the arrestees that are observed by the local level but unobserved by ICE agents. Naturally, ICE agents cannot condition on these. Part, however, may be observed by ICE. Assumption 1 thus amounts to ruling out commitment by ICE, at the stage in which it is informed about a person of interest and must decide to act on this information. For example, forward-looking ICE agents might to want make inter-temporal promises of lenient future behavior to obtain the sheriff's present collaboration over an individual they believe the local level may not want to remove. When a new fingerprint match arrives, we believe it is unlikely that ICE agents will be able to keep such a promise. This is particularly so because, on average, each ICE enforcement district is simultaneously responsible for more than a hundred different counties. Thus, we observe

$$\mathbb{P}(\text{Detainer}|\text{Arrest}) = (\pi^{H\ell} + \pi^{Hh})f \equiv P_{D|A} \tag{2}$$

at the county×time period level. Equation (2) shows that $P_{D|A}$ varies over time either through changes in federal enforcement f, or through changes in the composition of the pool of arrestees.

After ICE has issued detainers, the resulting distribution of detainers can be represented by the second table on the left of Figure 2. This distribution does not depend on f because the federal level does not select detainers based on local level preferences. It does not have L types either, which the federal level has filtered out. Now county-level officials must decide whether to honor the detainer. The county is happy to hand in Hh type arrestees: $\mathbb{P}(\text{ICE Custody}|\text{Detainer}, Hh) = 1$. In contrast, there is conflict over ℓ types, which the county may not want to hand in. The county's willingness to enforce immigration can be captured by the conditional probability of honoring such detainers: $\mathbb{P}(\text{ICE Custody}|\text{Detainer}, H\ell) \equiv g$. As such, the probability of observing detainers

[30] Notice that this is not an assumption. It simply corresponds to the definition of an L type.

translate into ICE custodies is

$$\mathbb{P}(\text{ICE Custody}|\text{Detainer}) = 1 \times \frac{\pi^{Hh}}{\pi^{H\ell} + \pi^{Hh}} + g \times \frac{\pi^{H\ell}}{\pi^{H\ell} + \pi^{Hh}} \equiv P_{C|D} \tag{3}$$

We also observe $P_{C|D}$ at the county×time period level. $P_{C|D}$ can vary over time because among H types the pool of arrestees is shifting between h and ℓ types, or because local immigration enforcement g is changing, or both: changes in the rate at which detainers translate into ICE custodies may be driven by changes in local enforcement or selection. Crucially, the full discretion of the local level in honoring detainers provides us with an exclusion restriction: $P_{C|D}$ does not vary with federal immigration enforcement f.

Once in ICE custody, removal decisions depend on ICE and immigration court efforts. Although individuals in custody are all H types, ICE and the courts may have misaligned preferences. To be fully general we must allow court-stage removal rates to vary with the remaining source of unobserved heterogeneity: $q^j \equiv \mathbb{P}(\text{Removal}|\text{ICE Custody}, \text{Detainer}, j)$, $j \in \{\ell, h\}$, denotes the conditional probability of removal of an Hj type. Both of these conditional probabilities will in general be interior. They will depend on the intensity of federal enforcement, and on the preferences of the district courts. They will not, however, depend on local enforcement, which constitutes an additional exclusion restriction implied by the pipeline. The conditional removal probability among people in ICE custody for whom a detainer was issued is

$$\mathbb{P}(\text{Removal}|\text{ICE Custody}, \text{Detainer}) = q^{\ell} \frac{g\pi^{H\ell}}{g\pi^{H\ell} + \pi^{Hh}} + q^{h} \frac{\pi^{Hh}}{g\pi^{H\ell} + \pi^{Hh}} \equiv P_{R|C,D} \tag{4}$$

We also observe this conditional probability. It will vary with court and federal immigration enforcement (through (q^{ℓ}, q^{h})), with local immigration enforcement (through g), and with the distribution of types in the pool of arrestees. Equation (4) reveals an important pattern of selection induced by the structure of the immigration enforcement pipeline: if the courts' preferences are strongly aligned with the county's preferences ($q^h > q^{\ell}$), then all else equal, a fall in local immigration enforcement, g, will *increase* $P_{R|C,D}$ even if the distribution of types and court and federal enforcement remain constant. The reason is a screening effect from local immigration enforcement over the pool of people in ICE custody: when the county reduces enforcement, the share of $H\ell$ individuals handed into ICE custody falls. The pool of custodies becomes selected towards Hh individuals, which courts are more willing to remove.

4.1.2 Partial Identification from the Detainer Track

Our analysis allowed us to relate three observable conditional probabilities, $(P_{D|A}, P_{C|D}, P_{R|C,D})$ to four enforcement intensity rates (f, g, q^{ℓ}, q^{h}) and the fraction of $H\ell$ and Hh types in the pool of arrested immigrants. We can conveniently re-express them in the following way:

$$x_1 \equiv P_{D|A} = (\pi^{H\ell} + \pi^{Hh})f \tag{5}$$

$$x_2 \equiv P_{D|A}P_{C|D} = (g\pi^{H\ell} + \pi^{Hh})f \tag{6}$$

$$x_3 \equiv P_{D|A}P_{C|D}P_{R|C,D} = (q^\ell g\pi^{H\ell} + q^h\pi^{Hh})f \tag{7}$$

Equations (5)-(7) provide us with two independent relationships between these observable probabilities and the unobservable enforcement rates: Taking the ratio of equations (5) and (6) for a county-time period with a positive number of ICE custodies,

$$\frac{\pi^{Hh}}{\pi^{H\ell}} = \frac{x_2 - x_1 g}{x_1 - x_2}. \tag{8}$$

Taking the ratio of (6) to (7) for a county-time period with a positive number of removals,

$$\frac{\pi^{Hh}}{\pi^{H\ell}} = \frac{(x_3 - x_2 q^\ell)g}{x_2 q^h - x_3}. \tag{9}$$

Equating these ratios we obtain the following relationship between (g, q^ℓ, q^h) and observables:

$$g = \frac{x_3 - x_2 q^h}{x_3 - x_2 q^\ell - x_1(q^h - q^\ell)} \tag{10}$$

Crucially, this relationship does not depend on the composition of the pool of arrestees $(\pi^{Hh}, \pi^{H\ell})$. By exploiting the variation across steps of the immigration enforcement pipeline along the detainer track, we obtain a relationship between local and court-enforcement probabilities that is purged of any selection issues. This is convenient because $(\pi^{Hh}, \pi^{H\ell})$ is unobserved and can be correlated with the enforcement choices at all the different stages. The manifold described by equation (10) provides a partial identification set for the three enforcement probabilities, provided that $x_1, x_2, x_3 > 0$. Finally, notice also that the ratio $\pi^{Hh} / \pi^{H\ell}$ is a measure of the extent of *preference alignment* between the federal and the local levels. From equation (8), if we can recover g, we will also have recovered the preference alignment ratio non-parametrically.

4.1.3 The Direct Track

Parallel to the issuance of detainers under Secure Communities, ICE also visits jails and prisons directly attempting to bring unlawfully present immigrants into custody. The Criminal Alien Program (CAP) is one of the main enforcement vehicles through which these efforts are implemented. Resource and political economy constraints limit the extent to which ICE issues detainers towards H types. Under Secure Communities, after ICE is informed of a fingerprint match and decides not to issue a detainer, it may subsequently employ the 'direct track' over the corresponding arrested immigrant. Thus, the 'direct track' is employed only over those fingerprint matches (arrests) for which no detainer was issued, when ICE officials find it in their interest to attempt taking some of the remaining H types into custody through other means.

The left-over pool of arrested individuals over which the direct track may apply is represented by the distribution in the second table to the right of Figure 2. Similar to the detainer track, only H types are at play as ICE has no interest over L types. Although ICE and the county have aligned preferences over Hh types, ICE has limited resources and in general will not undertake visits to all prisons continuously. We refer to v^d as the baseline *federal enforcement district level* probability of an ICE visit to a jail or prison. In other words, v^d is the district-specific component of the underlying technology through which ICE agents visit local detention facilities searching for unlawfully present immigrants who did not receive a detainer request. Conditional on a visit, the local level will want to collaborate over any Hh types requested. Thus, unconditionally, $\mathbb{P}(\text{ICE Custody}|\text{No Detainer}, Hh) = v^d$. In contrast, the local level may attempt to resist handing over $H\ell$ arrestees. We will call k the probability that an $H\ell$ type is successfully taken into ICE custody conditional on a visit. Notice that k must depend on a combination of federal and local efforts[31]. Thus, unconditionally, $\mathbb{P}(\text{ICE Custody}|\text{No Detainer}, H\ell) = v^d k$. As such, we observe

$$\mathbb{P}(\text{ICE Custody}|\text{No Detainer}) = v^d \frac{(1-f)\pi^{Hh}}{1-(\pi^{Hh}+\pi^{H\ell})f} + v^d k \frac{(1-f)\pi^{H\ell}}{1-(\pi^{Hh}+\pi^{H\ell})f} \equiv P_{C|ND} \qquad (11)$$

The detainer and direct tracks are, naturally, not independent. By making the direct track probability k depend on both federal and local-level immigration enforcement efforts, we allow it to be dependent with the detainer track probabilities f and g. $P_{C|ND}$ varies with federal immigration enforcement efforts (through v^d, k, and f), with local immigration enforcement efforts (through k), and with the composition of types in the population of arrestees. As a consequence of this filtering, the resulting pool of individuals in ICE custody from the direct track is represented by the third table to the right of Figure 2. This distribution does not depend on v^d because the likelihood of a prison visit applies equally for both h and ℓ types. Once in ICE custody, ICE and the court system determine whether these individuals are deported. Our second and last substantial assumption will be that once under ICE custody, conditional on observables (in particular offense severity) and type $\{h, \ell\}$, the track through which the arrestee reached ICE custody is irrelevant for the court's removal decision:

Assumption 2. *The probability of removal conditional on being under ICE custody does not depend on the track. For $j \in \{h, \ell\}$,*

$$\mathbb{P}(\textit{Removal}|\textit{ICE Custody, Detainer}, j) = \mathbb{P}(\textit{Removal}|\textit{ICE Custody, No Detainer}, j) \equiv q^j.$$

[31] This allows us to capture in a reduced-form way strategic considerations by ICE agents. For example, they may decide to forgo issuing a detainer request so as not to alert local police agencies of a possible visit.

We believe assumption 2 is very weak. Once in ICE custody, all individuals are H types that federal law enforcement is interested in removing. The submission of a detainer could signal a special interest of ICE in the unlawfully present individual. It could also signal, however, the county's interest in collaborating with the federal level. Thus, conditional on crime severity, the informational content of a detainer issuance is not unambiguous. It is unlikely that courts may want to discriminate between otherwise similar cases of people already in federal custody based only on how they landed into ICE custody. Moreover, recall from section 3 that both detainer and direct tracks exhibit similar patterns of change in the rates at which ICE custodies translate into removals, suggesting similar behavior by the immigration courts. Under this assumption, we can express the observed probability of a removal conditional on being in ICE custody as

$$\mathbb{P}(\text{Removal}|\text{ICE Custody, No Detainer}) = q^\ell \frac{k\pi^{H\ell}}{k\pi^{H\ell}+\pi^{Hh}} + q^h \frac{\pi^{Hh}}{k\pi^{H\ell}+\pi^{Hh}} \equiv P_{R|C,ND} \tag{12}$$

$P_{R|C,ND}$ varies with court enforcement -through (q^ℓ, q^h)-, with federal enforcement -through (q^ℓ, q^h), and k-, with local enforcement -through k-, and with changes in the distribution of types.

4.1.4 Partial Identification from the Direct Track

Our analysis of the immigration enforcement pipeline along the direct track allows us to relate two conditional probabilities $(P_{C|ND}, P_{R|C,ND})$ to five enforcement intensity rates (v^d, f, k, q^ℓ, q^h), and the fraction of $H\ell$ and Hh types in the pool of unlawfully present individuals arrested by local law enforcement. We can re-write these probabilities as:

$$y_1 \equiv P_{C|ND} = v^d \frac{1-f}{1-(\pi^{Hh}+\pi^{H\ell})f}\left[k\pi^{H\ell}+\pi^{Hh}\right] \tag{13}$$

$$y_2 \equiv P_{R|C,ND}P_{C|ND} = v^d \frac{1-f}{1-(\pi^{Hh}+\pi^{H\ell})f}\left[q^\ell k\pi^{H\ell}+q^h\pi^{Hh}\right] \tag{14}$$

Taking their ratio for a county-time period where the number of removals is not zero, dividing both numerator and denominator by $\pi^{H\ell}$, and using equation (8), we can replace for the preference alignment ratio $\pi^{Hh} / \pi^{H\ell}$, and solve for k:

$$k = \frac{(x_2 - x_1 g)}{(x_1 - x_2)} \frac{(y_1 q^h - y_2)}{(y_2 - y_1 q^\ell)} \tag{15}$$

Equation (15) shows that k is pinned down by the observables of both detainer and direct tracks, and (g, q^h, q^ℓ). Finally, dividing equation (13) through by equation (5) and replacing for k from equation (15), we eliminate the preference alignment ratio to obtain:

$$v^d\left(\frac{1-f}{f}\right) = \frac{(1-x_1)(1-g)}{(x_2-x_1 g)} \frac{(y_2 - y_1 q^\ell)}{(q^h - q^\ell)} \tag{16}$$

Equation (16) shows that the inverse odds ratio of federal enforcement f is pinned down up to scale by the observables of both detainer and direct tracks, and (g, q^h, q^ℓ). The comparison of rates at which individuals with and without detainers in ICE custody are removed contains the information that allows us to learn about f.

We purge selection from equations (10), (15), and (16) by taking ratios of conditional probabilities across steps of the pipeline. This relies on our ability to track the implied changes in the composition of the underlying pool of individuals moving along it *within* time periods. In an analogy to linear panel settings where taking first differences eliminates fixed effects, here we eliminate the unobserved heterogeneity by taking quotients of steps along the pipeline.

5 Identification and Estimation

Our analysis from section 4 shows that the detainer and direct tracks provide us with three relationships (equations (10), (15), (16)) between observable conditional probabilities of transition across stages of the pipeline, $(x_{1ct}, x_{2ct}, x_{3ct}, y_{1ct}, y_{2ct})$, and the six key unobserved immigration enforcement probabilities $(g_{ct}, f_{ct}, k_{ct}, q^\ell_{ct}, q^h_{ct}, v^d_t)$ for each county-time period (c, t). Crucially, our strategy has allowed us to purge these relationships from the composition of the pool of arrestees $(\pi^{Hh}_{ct}, \pi^{H\ell}_{ct})$ *period by period*, so even changes over time in what constitutes a high or low priority individual for the federal or local levels are controlled for. Any endogenous response of the supply of offenses, or of the arresting behavior of law enforcement to immigration enforcement changes, which can directly change the composition of the arrest pool, are similarly controlled for. Thus, our empirical strategy does not assume the exogeneity of criminal or arresting behavior. Cross-county migration of unlawfully present immigrants in response to immigration enforcement pressure in neighboring counties can also impact the arrest pool composition, and thus are controlled for as well. When allowing for unobserved preference misalignment, the structure of the immigration enforcement pipeline and the observed data allow us to control for selection completely non-parametrically, but do not provide enough information to identify each enforcement probability separately. However, notice the triangular structure implied by equations (10), (15), and (16): A given pair (q^h_{ct}, q^ℓ_{ct}) pins down g_{ct}, and knowledge of g_{ct} then pins down k_{ct} and $v^d_t(1 - f_{ct})/f_{ct}$. Moreover, for any sequence $\{g_{ct}\}_{t=1}^T$, we recover the time series of preference alignments $\{\pi^{Hh}_{ct} / \pi^{H\ell}_{ct}\}_{t=1}^T$ using equation (8). We now characterize the identified set for (q^h_{ct}, q^ℓ_{ct}):

Proposition 1. *Suppose that* $x_{1ct} > x_{2ct} > x_{3ct} > 0$ *and* $y_{1ct} > y_{2ct} > 0$*, and define* $\underline{m} \equiv min\{x_{3ct}/x_{2ct}, y_{2ct}/y_{1ct}\}$*,* $\overline{m} \equiv max\{x_{3ct}/x_{2ct}, y_{2ct}/y_{1ct}\}$*, and* $\tilde{q} = (x_{1ct}y_{2ct} - x_{3ct}y_{1ct})/y_{1ct}(x_{1ct} - x_{2ct}))$*. The observed vector of conditional probabilities* $\mathbf{w}_{ct} = (x_{1ct}, x_{2ct}, x_{3ct}, y_{1ct}, y_{2ct})$ *for a given county-period is consistent with any pair* $(q^h, q^\ell) \in \mathcal{R}(\mathbf{w}_{ct})$*, where* $\mathcal{R}(\mathbf{w}_{ct}) = \mathcal{R}_1 \cup \mathcal{R}_2$*, and:*

$$\mathcal{R}_1 = \left\{(q^h, q^\ell) : q^h < \underline{m}, \text{ and } q^\ell > max\{\overline{m}, \tilde{q}\}\right\}$$

$$\mathcal{R}_2 = \left\{(q^h, q^\ell) : q^h > \overline{m},\ \ and\ q^\ell < min\{\underline{m}, \tilde{q}\}\right\}.$$

Proof. See Appendix A. $\square$

This result follows from jointly imposing all the constraints relating observed moments to unobserved probabilities. This includes the relationships in equations (10), (15), and (16) implied by the immigration enforcement pipeline, together with all probabilities lying inside the unit interval. Each identified set has the same geometric structure, which we illustrate in Figure B.3: two disjoint rectangles, one above and one below the 45-degree line. Its shape illustrates the reason for the lack of non-parametric point identification of the enforcement probabilities based on the immigration pipeline alone: observed conditional probabilities are consistent with a high removal rate for ℓ types and a low removal rate for h types, or vice versa.

5.1 Recovering Enforcement Efforts

We have not yet incorporated into our analysis the relationships across the enforcement probabilities $(g_{ct}, f_{ct}, k_{ct}, v_t^d, q_{ct}^\ell, q_{ct}^h)$ that are also implied by the immigration enforcement process, and driven by the unobserved enforcement effort choices of the local and federal levels. First, the sources of covariation between probabilities: across the detainer and direct tracks, i) g_{ct} should covary with k_{ct} through the immigration enforcement effort of the local level; ii) f_{ct} should covary with k_{ct} through the immigration enforcement effort of the federal level; iii) q_{ct}^ℓ and q_{ct}^h should covary with f_{ct} through the immigration enforcement effort of the federal level. Second, the following exclusion restrictions: i) g_{ct} should not vary with federal enforcement efforts; ii) f_{ct} should not vary with local enforcement efforts; iii) v_t^d should not vary across counties within a federal enforcement district; iv) q_{ct}^ℓ and q_{ct}^h should not vary with local enforcement efforts.

We exploit the information from these additional implications of the deportation process through parametric restrictions. We denote the local level enforcement effort by ϵ_{ct}, and the federal level enforcement effort by ξ_{ct}. For computational convenience, we model the enforcement probabilities as logistic functions of observable county characteristics and semester dummies, $\mathbf{x}_{ct}$, and the corresponding enforcement efforts. We can directly work with the log odds forms:

$$\log\left(\frac{f_{ct}}{1-f_{ct}}\right) \equiv \tilde{f}_{ct} = \mathbf{x}_{ct}'\boldsymbol{\beta}^f + \xi_{ct} \tag{17}$$

$$\log\left(\frac{g_{ct}}{1-g_{ct}}\right) \equiv \tilde{g}_{ct} = \mathbf{x}_{ct}'\boldsymbol{\beta}^g + \epsilon_{ct} \tag{18}$$

$$\log\left(\frac{k_{ct}}{1-k_{ct}}\right) \equiv \tilde{k}_{ct} = \mathbf{x}_{ct}'\boldsymbol{\beta}^k + \kappa_\epsilon\epsilon_{ct} + \kappa_\xi\xi_{ct} + \eta_{ct} \tag{19}$$

$$\log\left(\frac{q_{ct}^\tau}{1-q_{ct}^\tau}\right) \equiv \tilde{q}_{ct}^\tau = \mathbf{x}_{ct}'\boldsymbol{\beta}^{q\tau} + \gamma^\tau\xi_{ct} + \zeta_{ct}^\tau, \qquad \tau \in \{\ell, h\} \tag{20}$$

where $\boldsymbol{\beta} \equiv (\boldsymbol{\beta}^f, \boldsymbol{\beta}^g, \boldsymbol{\beta}^k, \boldsymbol{\beta}^{qh}, \boldsymbol{\beta}^{q\ell})$, the $(\boldsymbol{\beta}, \kappa_\epsilon, \kappa_\xi, \gamma^h, \gamma^\ell)$ are regression coefficients, and (η_{ct}, ζ_{ct}) are errors.[32] The ζ_{ct}^τ capture the enforcement efforts of immigration courts unrelated to ICE efforts. Recall from equation (16) that we do not directly have an expression for f_{ct}, but rather for $\overline{f}_{ct} \equiv v_t^d(1 - f_{ct})/f_{ct}$. Re-writing equation (17) in terms of $\overline{f}_{ct}$,

$$\log(\overline{f}_{ct}) \equiv \tilde{\overline{f}}_{ct} = \log(v_t^d) - \mathbf{x}_{ct}'\boldsymbol{\beta}^f - \xi_{ct} \tag{21}$$

so district fixed effects in equation (21) recover the district-level 'prison visit' probabilities.

Suppose we knew (q_{ct}^ℓ, q_{ct}^h) for all (c,t), which we collect in the vectors $(\mathbf{q}^\ell, \mathbf{q}^h)$. Then we could directly compute g_{ct}, $\tilde{\overline{f}}_{ct}$, and k_{ct} for each (c,t), allowing us to estimate the regressions in equations (18) and (21). From these we could then recover the ϵ_{ct} and ξ_{ct} as residuals:

$$\hat{\xi}_{ct} = \delta_{t,ols}^d - \mathbf{x}_{ct}'\boldsymbol{\beta}_{ols}^f - \tilde{\overline{f}}_{ct}, \qquad \hat{\epsilon}_{ct} = \tilde{g}_{ct} - \mathbf{x}_{ct}'\boldsymbol{\beta}_{ols}^g$$

where $\delta_{t,ols}^d$ are federal district by period fixed effects. A plot of the ϵ_{ct} on the ξ_{ct} over time for a given county would then reveal the shape of the county's response to the federal effort. The vectors of immigration enforcement efforts $\hat{\boldsymbol{\xi}}(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X})$ and $\hat{\boldsymbol{\epsilon}}(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X})$ are thus closed-form functions of $(\mathbf{q}_{ct}^\ell, \mathbf{q}_{ct}^h)$, $\mathbf{W} = (\mathbf{w}_1, ..., \mathbf{w}_n)$ where $\mathbf{w}_c = (\mathbf{w}_{c1}', ..., \mathbf{w}_{ct}')'$, and $\mathbf{X} = (\mathbf{x}_1', ..., \mathbf{x}_n')'$. Using these enforcement efforts as regressors, we could then estimate regressions (19)-(20). The minimized sums of squared residuals of these regressions are thus closed-form functions of $(\mathbf{q}_{ct}^\ell, \mathbf{q}_{ct}^h)$, $\mathbf{W}$, and $\mathbf{X}$ exclusively:

$$\begin{aligned}
\mathcal{S}^k(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) &= \sum_c \sum_t (\tilde{k}_{ct} - \mathbf{x}_{ct}'\boldsymbol{\beta}_{ols}^k - \kappa_{\epsilon,ols}\hat{\epsilon}_{ct} - \kappa_{\xi,ols}\hat{\xi}_{ct})^2 \\
\mathcal{S}^\ell(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) &= \sum_c \sum_t (\tilde{q}_{ct}^\ell - \mathbf{x}_{ct}'\boldsymbol{\beta}_{ols}^{q\ell} - \gamma_{ols}^\ell\hat{\xi}_{ct})^2 \\
\mathcal{S}^h(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) &= \sum_c \sum_t (\tilde{q}_{ct}^h - \mathbf{x}_{ct}'\boldsymbol{\beta}_{ols}^{qh} - \gamma_{ols}^\ell\hat{\xi}_{ct})^2
\end{aligned}$$

We can define $\mathcal{S} = \mathcal{S}^k + \mathcal{S}^\ell + \mathcal{S}^h$, and proceed to choose the vectors $(\mathbf{q}^\ell, \mathbf{q}^h)$ to maximize the fit of equations (19)-(20) over the identified sets $\mathcal{R}(\mathbf{w}_{ct})$ for each observation:

$$\min_{(\mathbf{q}^\ell, \mathbf{q}^h) \in \times_{ct}\mathcal{R}(\mathbf{w}_{ct})} \mathcal{S}(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) \tag{22}$$

This is a high-dimensional search. However, our objective function is in closed form, and easily evaluated at any given $(\mathbf{q}^\ell, \mathbf{q}^h)$. It is also strictly convex and thus has a unique minimum. Moreover, the search over each element of the vectors $(\mathbf{q}^\ell, \mathbf{q}^h)$ is highly constrained by its corresponding identified set $\mathcal{R}(\mathbf{w}_{ct})$. Our ability to go from the partial identification result in Proposition 1 to

[32] The logistic choice allows us to recover the relevant coefficients as closed forms from the corresponding log odds linear regressions, but any choice of functional form for the enforcement probabilities would suffice.

the point identification result from the solution to equation (22) relies on two features of equations (17)-(20): i) the exclusion restrictions provided by the immigration enforcement pipeline allowing us to recover the unobserved enforcement efforts of the local and federal levels at a given pair $(\mathbf{q}^{\ell}, \mathbf{q}^{h})$; ii) the assumption that the coefficients $\boldsymbol{\beta}$ on the county characteristics in these equations (which capture the heterogeneity along observables in the response of the enforcement probabilities to the local and federal efforts) are homogeneous across counties. The constancy of these coefficients across counties implies that at a given $(\mathbf{q}^{\ell}_{-ct}, \mathbf{q}^{h}_{-ct})$ for all county-periods except for (c, t), the implied value of $\boldsymbol{\beta}$, common across all observations, pins down what the best pair $(q^{\ell}_{ct}, q^{h}_{ct}) \in \mathcal{R}(\mathbf{w}_{ct})$ must be for solving equation (22).

We implement this procedure separately for minor and serious offenses, recovering federal and local enforcement efforts over both: $(\boldsymbol{\xi}^{m}, \boldsymbol{\xi}^{s})$ and $(\boldsymbol{\epsilon}^{m}, \boldsymbol{\epsilon}^{s})$.[33] We then recover the implied immigration enforcement probabilities for minor and serious offense cases $\{\mathbf{g}, \boldsymbol{f}, \mathbf{k}, \mathbf{q}^{\ell}, \mathbf{q}^{h}, \mathbf{v}^{d}\}_{m}$, $\{\mathbf{g}, \boldsymbol{f}, \mathbf{k}, \mathbf{q}^{\ell}, \mathbf{q}^{h}, \mathbf{v}^{d}\}_{s}$, and the corresponding strengths of covariation between these probabilities –$(\kappa^{m}_{\epsilon}, \kappa^{m}_{\xi}, \gamma^{\ell,m}, \gamma^{h,m})$ and $(\kappa^{s}_{\epsilon}, \kappa^{s}_{\xi}, \gamma^{\ell,s}, \gamma^{h,s})$–. Finally, we recover the coefficients $(\boldsymbol{\beta}_{m}, \boldsymbol{\beta}_{s})$ capturing the patterns of heterogeneity in the effects of local and federal enforcement efforts across observable characteristics, on the immigration enforcement probabilities.

Identification of the regression coefficients and distributions of local and federal enforcement efforts from equations (17)-(20) follows from comparing the implied rates of movement along steps of the pipeline of counties with similar characteristics. When, for example, two similar counties face different implied values for f_{ct}, we can attribute it to differences in federal efforts, ξ_{ct}, because these relationships have already controlled for selection as they do not depend on $(\pi^{H\ell}, \pi^{Hh})$.

6 Estimation Results

Our empirical strategy allows us to recover the local immigration enforcement response to changes in federal immigration enforcement efforts. We do so exploiting the variation in rates at which arrested unlawfully present individuals move along the deportation process, allowing us to control for selection. This strategy, however, is demanding on the data. As Proposition 1 indicates, we can only purge selection from periods in which we observe strictly positive counts of immigration enforcement activity at all stages of the immigration enforcement pipeline. This, naturally, limits the external validity of our findings. The sample for which periods with positive counts of detainers, ICE custodies with and without detainers, and removals with and without detainers are all positive, is composed of counties with relatively large populations, and relatively large populations of unlawfully present immigrants.

In panel B of Table B.2 we report summary statistics for the resulting sample of counties with

[33] We use a particle swarm optimizer to minimize equation (22), which is ideal for optimizing a high-dimensional function inside a bounded support.

Panel A:	Pre-Policy Change (2009-I – 2011-I)				Post-Policy Change (2011-II – 2014-II)			
	Minor Offenses		Serious Offenses		Minor Offenses		Serious Offenses	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
f	0.25	0.30	0.03	0.09	0.22	0.27	0.12	0.24
g	0.28	0.26	0.54	0.31	0.26	0.27	0.43	0.29
q^l	0.52	0.31	0.44	0.31	0.57	0.29	0.49	0.27
q^h	0.69	0.28	0.72	0.27	0.68	0.25	0.73	0.27
v^d	2.35	2.73	0.31	0.36	1.55	2.24	1.69	2.35
k	0.15	0.32	0.07	0.23	0.22	0.35	0.13	0.31
$\pi^{Hh}/\pi^{H\ell}$	0.33	0.94	0.35	0.99	0.30	0.67	0.23	0.69
Observations	448		189		1,900		912	

Panel B:	Coefficients of Interest			
	Minor Offenses		Serious Offenses	
κ_ϵ	-0.25	(0.016)	-0.25	(0.032)
κ_ξ	1.04	(0.052)	0.96	(0.043)
γ^l	0.26	(0.058)	0.11	(0.047)
γ^h	-0.19	(0.051)	-0.27	(0.030)
Observations	2,348		1,101	

Table 2: Summary Statistics for Estimated Enforcement Probabilities and Coefficients. The table presents summary statistics for enforcement variables and coefficient estimates of key parameters of interest. The first two columns of Panel A report means and standard deviations for minor offenses in the pre-guidelines period, i.e. from the first semester of 2009 to the first semester of 2011. The second two columns of Panel A refer to serious offenses for the same period. The first two columns of Panel B present means and standard deviations for minor offenses in the post-guidelines period, i.e. from the second semester of 2011 to the second semester of 2014. The second two columns of Panel B refer to serious offenses for the same period. Panel C reports coefficients for the logistic regressions in equations (19) and (20), for minor and serious offenses. Standard errors for these coefficients, reported in parentheses, account for the presence of generated regressors in equations (19) and (20) (see subsection A.2).

observed data satisfying the conditions required for identification. Our estimation sample is composed of counties with somewhat larger populations than the average county, and 30 percent larger undocumented population than the average county (2.2 compared to 1.7 percent undocumented share). It is also slightly more educated, but not much more Democratic than the average county (43 compared to 41 percent Democratic share). However, the average county in our sample is considerably less rural than average, and has a significantly larger services sector. The results below are not representative of the smaller, more rural communities in the US. Figure B.4 similarly presents a county-level map of the US, where we highlight the counties included in this sample. Despite the limitations just highlighted, the map reveals a wide regional coverage. As expected, Texas, Florida, the Southwestern US and the Northeast are heavily represented in our estimation sample. In Appendix Table B.4 we also report summary statistics for the data moments $\mathbf{w}_{ct}$ in our estimation sample. On average, enforcement outcomes are lower in the post-guidelines period at every stage along the immigration enforcement pipeline, except for minor offenses in the direct track. Perhaps surprisingly, these average falls are larger for serious offenses. Along the detainer track, for example, the probability of a removal at the mean fell from 8.3 to 5.1 percent; it fell even more along the direct track, from 33 to 19 percent. Our empirical strategy allows us to decompose the sources of variation driving these changes.

	Dependent Variable: Local Effort ϵ_{ct}			
	Minor Offenses		Serious Offenses	
	Pooled	County FE	Pooled	County FE
	(1)	(2)	(3)	(4)
Federal effort ξ_{ct}	-1.15	-1.32	-0.55	-0.63
	(0.04)	(0.05)	(0.05)	(0.05)
R squared	0.24	0.49	0.15	0.38
Observations	2,348		1,101	

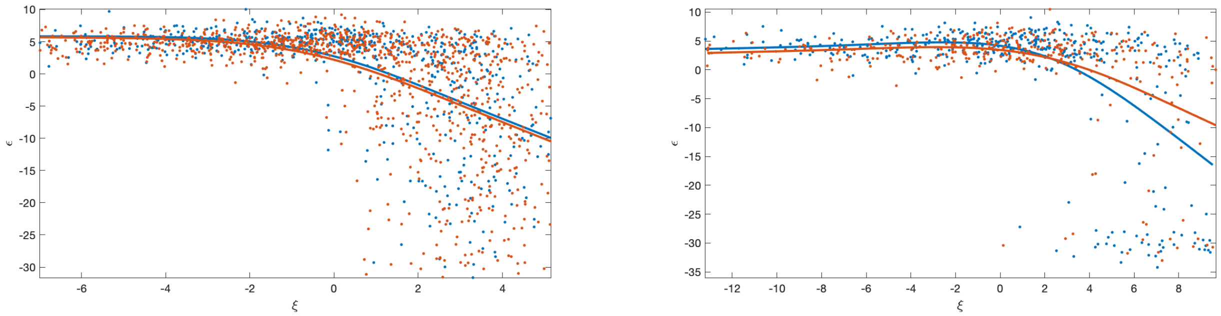
Table 3: Local Best Responses: Pooled vs. Fixed Effects. The table presents coefficients from county-level regressions of local immigration enforcement effort ϵ on federal immigration enforcement effort ξ. Odd columns present pooled estimates, while even columns present county fixed-effects estimates. The first two columns present results for minor offenses, while the last two columns present results for serious offenses. Standard errors for these coefficients are reported in parentheses.

6.1 Enforcement Probabilities and Best Responses

In panel A of Table 2 we present average estimates of the immigration enforcement rates by type of offense and period. Panel B reports the estimated coefficients from equations (19) and (20) capturing the covariation between local and federal enforcement along the detainer and direct tracks, and between federal efforts and immigration court outcomes.[34] Average detainer issuance rates f fell 3 percentage points for minor offenses after the guidelines were issued, and increased 9 percentage points for serious offenses. These changes are in line with the purported objective of ICE's change in guidelines, but for minor offenses are smaller than the guidelines themselves suggested. Especially for serious offenses, we find a large change in the average rate of compliance with detainers, g, which fall by 11 percentage points. On the other hand, we estimate falls in average preference alignment $\pi^{Hh}/\pi^{H\ell}$ for both levels of offenses, with an especially large fall for serious offenses. This suggests that while the fall in immigration enforcement outcomes related to minor offenses following the change in guidelines was mostly driven by the relaxation of federal efforts, the fall in immigration enforcement outcomes related to serious offenses was driven by an offsetting response of the local level to increased federal efforts over these types of cases, and a concomitant increase in conflict between levels.

It is likely that a major force driving the fall in alignment over serious offenses was a change in ICE's removal priorities related to offense severity. If an individual who previously was not of interest to ICE, and thus, about whom there was little disagreement between the federal and local levels, becomes of interest to ICE, this creates a divergence in the preferences of both levels over the case. The table also suggests that the federal level increased enforcement over serious offenses along both detainer and direct tracks (average k increased by 6 percentage points). This is consistent with the decreased collaboration of the local level, because avoiding the use of detainers through the direct track partially allowed ICE to undermine local level resistance.

[34] In Tables Table B.5 and Table B.6 we report the corresponding estimates of the $\boldsymbol{\beta}$ coefficients on our vector of covariates in equations (17)-(20). Our inference for the coefficients in these equations accounts for the presence of ϵ and ξ as generated regressors. We present the derivation of these analytic standard errors in Appendix A.2.



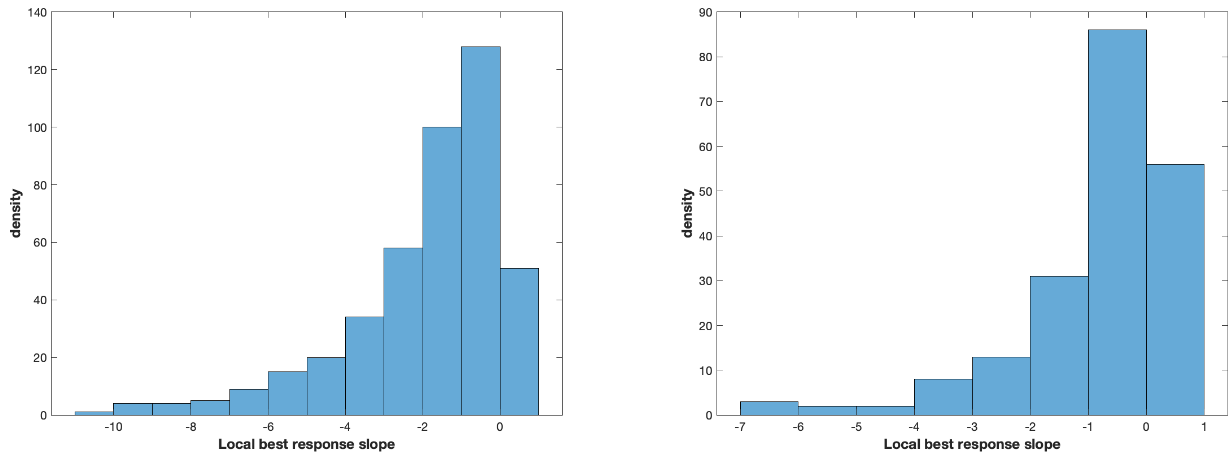
(a) Minor offenses **(b)** Serious offenses

Figure 3: Scatterplot of Local Efforts on Federal Efforts. Panel (a) shows the scatterplot corresponding to column (1) in Table 3, plotting ϵ on ξ for arrestees charged with minor (levels 2 and 3) offenses. Panel (b) shows the scatterplot corresponding to column (3) in Table 3, plotting ϵ on ξ for for arrestees charged with serious (level 1) offenses. Points in blue represent counties above median Democratic vote share, and points in red represent counties below median Democratic vote share. The curves are non-parametric best-fit regression lines for each group of counties.

Turning our attention to Panel B, we find that federal efforts lead to a positive covariation between f and k, while local efforts lead to a negative covariation between g and k. The table also suggests that immigration court preferences did not change with the introduction of the federal guidelines. These are more aligned with county-level than with federal-level preferences: at the mean, $q^h > q^\ell$. We find, however, that ξ leads to a negative covariation between f and q^h, and to a positive covariation between f and q^ℓ. When federal enforcement is high, the courts move towards making more likely the removal of individuals the local level would rather not deport.

We find strong evidence of strategic substitutabilities in the response of the local level to increased federal enforcement. Because our approach allows us to recover ξ and ϵ at different points in time for each county, and because the structure of the pipeline makes the county's collaboration decision happen *after* ICE has made a detainer decision, we can directly reconstruct movements along the 'best response' curve of the county. In Table 3 we present our main estimates of the average slope of this best response across counties, from models where we regress ϵ on ξ. We report separately the responses over each type of offense, finding substitutabilities in both cases, but larger responses for minor offenses. Even columns in the table report county fixed effects models, that effectively compute the slope for each county and average over those slopes. For minor offenses, we find that a one standard deviation higher federal enforcement leads to 1.3 standard deviations less local enforcement. For serious offenses, we find a similarly negative local level response of 0.6 standard deviations. The local level response in most counties partially undoes the federal effort. Both coefficients are precisely estimated.

We argued above that our empirical strategy allows us to distinguish selection from enforcement. In the odd columns of the table we report the results of running a pooled regression of ϵ on ξ, allowing us to indirectly assess the validity of our claim: in the pooled model, county-level fixed effects are in the error term. For both levels of offenses, the magnitudes of the pooled and fixed effects coefficients are very close to each other, showing that ξ is effectively uncorrelated



(a) Minor offenses **(b)** Serious offenses

Figure 4: Distribution of Best Response Slopes Across Counties. The figures show the distribution of county slopes for a regression of ϵ on ξ. Panel (a) is for cases of arrestees charged with minor (levels 2 and 3) offenses. Panel (b) is for cases of arrestees charged with serious (level 1) offenses.

with fixed county-level unobservables. The results from Table 3 motivate us to present in Figure 3 the scatterplots corresponding to the pooled regressions, where we distinguish between counties above (blue) and below (red) median Democratic vote share.

6.2 Heterogeneity in the Local Enforcement Response

Counties with different preferences should be expected to respond differently to federal enforcement. How much heterogeneity is there in the nature of the local-level enforcement response? Figure 4 plots the county-level distribution of slopes, which we recover directly from linearly fitting ϵ to ξ county by county. For both minor and serious offenses cases, around 80 percent of counties exhibit negative slopes, indicating strategic substitutability. The remainder 20 percent of counties show positive slopes, indicating strategic complementarity.

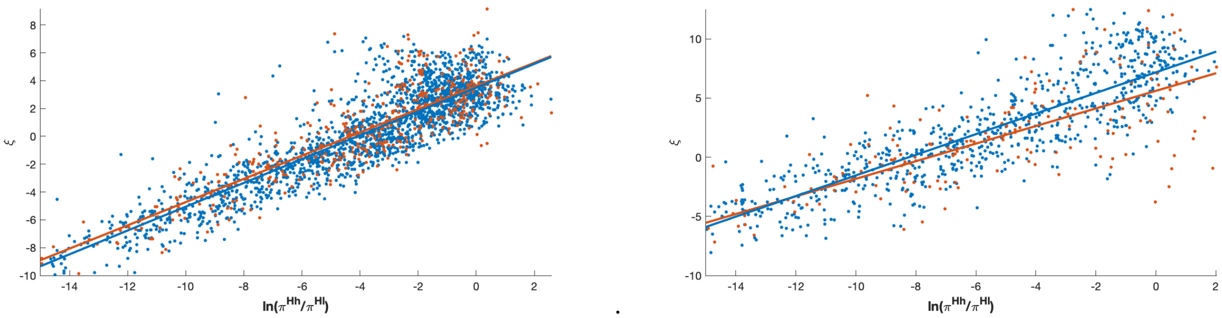
To investigate the main drivers of the heterogeneity in the shape of these best responses, in Table 4 we present results of cross-sectional regressions for the slopes of each county's best response on a battery of county characteristics related to local preferences over immigration policy. In columns 1 and 4 we include only a constant and the Democratic vote share (-50 percent). The constant captures the average best response slope for a perfectly competitive county. More Democratic counties exhibit significantly more negative best responses for serious offenses. In columns 2 and 5 we then add the Hispanic share of the population. Perhaps surprisingly, conditional on Democratic support, counties with larger Hispanic populations have less negative slopes for minor offenses. Lastly, in columns 3 and 6 we include the undocumented share (which is highly correlated with the Hispanic share), log population, the share with a bachelor's degree, a rural county dummy, the share of employment in the services sector, log distance to ICE and

Dependent Variable: County's Best Response Slope	Minor Offenses			Serious Offenses		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-1.86	-2.05	-3.38	-0.76	-0.72	-1.82
	(0.06)	(0.09)	(1.31)	(0.06)	(0.09)	(1.34)
Democratic party share	-0.19	-0.28	-1.32	-1.82	-1.81	-2.05
	(0.42)	(0.42)	(0.57)	(0.38)	(0.39)	(0.55)
Hispanic share		1.11	1.22		-0.20	-0.09
		(0.41)	(0.53)		(0.33)	(0.43)
Undocumented share			-0.29			9.93
			(4.07)			(4.07)
Log population			0.20			-0.03
			(0.08)			(0.08)
Bachelor degree share			0.55			0.67
			(0.89)			(0.82)
Rural			-0.57			-0.47
			(0.24)			(0.33)
Services share			-1.86			0.86
			(1.41)			(1.39)
Log distance ICE office			-0.02			0.03
			(0.02)			(0.02)
287(g) program			0.23			0.12
			(0.22)			(0.19)
R squared	0.0003	0.005	0.04	0.02	0.02	0.05
Observations		429			201	

Table 4: Heterogeneity in Local Best Responses. The table shows regression coefficients for the slopes of the best response of ϵ to ξ, for minor and serious offenses. The dependent variable in all specifications is the slope of a regression of ϵ on ξ and a constant for each county. Regressions are weighted by the number of time periods used to estimate each slope. The explanatory variables include a constant and the following characteristics: 2010 log population, the undocumented share 2010, the Democratic party share (2008-2012 average presidential vote shares minus 50 percent), the bachelor degree share, the Hispanic share, the services share (fraction of the employed population working in the services sector), a rural dummy (indicating whether the county is considered non-metropolitan according to the Center for Disease Control), log distance to ICE office (measured as the log of the number of miles between the county centroid and the county centroid of the corresponding ICE district office seat), and a 287(g) Program dummy (indicating whether the county or any city in the county was ever part of the 287(g) program) taken from Steil and Vasi (2014).

a dummy for the existence of a 287(g) cooperation agreement with the federal government. The inclusion of these controls makes the coefficient on the Democratic share negative for both kinds of offenses, making it clear that aggregate partisan preferences are the main driver of the local-level response. In counties with larger undocumented populations, in contrast, the best response for serious offenses is less negatively sloped.[35] These findings highlight the importance of the local response to federal enforcement efforts, and rationalize why immigration enforcement outcomes under Secure Communities varied widely across space.

[35]In principle an important covariate capturing political economy considerations is whether the county elects or appoints its sheriff. Among our sample of counties, however, 98 percent of them elect their sheriff so we omit this variable from our set of covariates.



(a) Minor offenses **(b)** Serious offenses

Figure 5: The Nature of Selection: Preference Alignment and Federal Immigration Enforcement Efforts. The figure shows the relationship between log preference alignment and federal immigration enforcement efforts, pooled across county-time periods. Panel (a) is for arrestees charged with minor (levels 2 and 3) offenses, and corresponds to the results reported in column (1) of panel A in Table 5. Panel (b) is for arrestees charged with serious (level 1) offenses, and corresponds to the results reported in column (1) of panel B in Table 5.

6.3 Patterns of Unobserved Heterogeneity

Now we discuss our findings related to the patterns of unobserved heterogeneity in immigration enforcement. Our measure of preference alignment, $\pi^{Hh}/\pi^{H\ell}$, is strongly positively correlated with federal immigration enforcement efforts ξ. We illustrate this in Figure 5 where we plot the unconditional scatterplots between both variables. Panel (a) presents the scatterplot for minor offenses, and panel (b) for serious offenses. We confirm the robustness of this correlation in the first three columns of Table 5. There we report panel regressions of federal efforts on preference alignment. The first column reports the unconditional relationship. In the second column we include county fixed effects, which slightly increase the magnitude of the estimated coefficient. The coefficient is 0.85 (s.e. $= 0.01$), for both minor and serious offenses.[36] This is a key result of our analysis. ICE is extremely good at targeting its enforcement efforts towards places where those efforts will be highly effective (where the composition of the arrest pool is such that ICE can expect a high degree of local-level cooperation). This is perhaps not as surprising considering the informational advantage that ICE acquired under Secure Communities and its access to massive law enforcement databases. At the same time, the strong willingness of the federal level to direct efforts toward places where it expects collaboration also indicates that the local level is a key gatekeeper for immigration enforcement.

In columns 4-9 of Table 5 we complement these results showing that the negative unconditional correlation between local efforts ϵ and preference alignment $\pi^{Hh}/\pi^{H\ell}$ is completely driven by federal immigration efforts ξ. Column 4 reports the unconditional regression coefficient, which is negative and statistically significant. This is also the case after introducing county fixed effects in columns 5-6. In columns 7-9, controlling for federal efforts ξ, the negative relationship between local efforts and preference alignment vanishes. We interpret this exercise as an additional speci-

[36]In column three we find no difference in this relationship before and after the change in ICE guidelines.

Dependent Variable:	Federal Effort ξ_{ct}			Local Effort ϵ_{ct}					
Panel A: Minor Offenses	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Log}(\pi^{Hh}/\pi^{H\ell})_{ct}$	0.85	0.95	0.94	-1.00	-1.23	-1.17	-0.14	0.34	0.37
	(0.008)	(0.009)	(0.01)	(0.04)	(0.05)	(0.07)	(0.10)	(0.16)	(0.17)
$\text{Log}(\pi^{Hh}/\pi^{H\ell})_{ct} \times \text{Guidelines}_t$			0.016			-0.07			-0.05
			(0.012)			(0.06)			(0.05)
Federal effort ξ_{ct}							-1.01	-1.65	-1.65
							(0.11)	(0.16)	(0.16)
County fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R squared	0.81	0.94	0.94	0.21	0.46	0.46	0.25	0.49	0.49
Observations		2,348				2,348			
Dependent Variable:	Federal Effort ξ_{ct}			Local Effort ϵ_{ct}					
Panel B: Serious Offenses	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Log}(\pi^{Hh}/\pi^{H\ell})_{ct}$	0.85	0.91	0.89	-0.45	-0.57	-0.57	0.16	0.08	0.08
	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.06)	(0.11)	(0.15)	(0.16)
$\text{Log}(\pi^{Hh}/\pi^{H\ell})_{ct} \times \text{Guidelines}_t$			0.013			-0.001			0.008
			(0.013)			(0.05)			(0.05)
Federal effort ξ_{ct}							-0.71	-0.72	-0.72
							(0.13)	(0.17)	(0.17)
County fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R squared	0.87	0.94	0.94	0.12	0.36	0.36	0.15	0.38	0.38
Observations		1,101				1,101			

Table 5: Correlation between preference alignment and immigration efforts. The table shows regression coefficients for panel regressions of federal and local immigration enforcement efforts on the log of preference alignment $\pi^{Hh}/\pi^{H\ell}$. Panel A reports results for cases involving minor offenses, while panel B reports results involving serious offenses. In columns 1-3 the dependent variable is the federal effort ξ. In columns 4-9 the dependent variable is the local effort ϵ. Columns 2, 3, 5-9 include county-level fixed effects. Columns 3, 6, and 9 additionally include an interaction term between preference alignment and a dummy for the period following the federal guidelines change. Columns 7-9 additionally include federal immigration efforts ξ as a regressor. The reported standard errors are robust to arbitrary heteroskedasticity.

fication test of our model. It reassures us that the best responses we recovered can be interpreted causally, and that our model of the immigration enforcement pipeline is a good approximation to the actual operation of the process.

6.4 The 2011 ICE Guidelines: Impact on Preferences and Removals

As we discussed in detail in section 2, the Obama administration issued new federal immigration enforcement guidelines in the summer of 2011. In a setting of policy federalism like the one we study here, evaluating the impacts of such a policy change is particularly challenging using, for example, a traditional difference in differences methodology: first, even if the changes in federal enforcement were applied uniformly across jurisdictions, heterogeneous local preferences imply differential responses along margins we may be unable to measure. We would not expect, moreover, for ICE to have changed its enforcement uniformly either. This constitutes an additional dimension of heterogeneity difficult to account for in the absence of a plausible model for the behavior of the federal level.

The approach we implemented above, however, allows us to quantify some of the impacts of

	Dependent Variable: Preference Alignment $\text{Log}(\pi^{Hh}/\pi^{H\ell})_{ct}$						
	Minor Offenses				Serious Offenses		
	(1)	(2)	(3)		(4)	(5)	(6)
$\text{Dem.}_c \times \text{Guidelines}_t$	-0.23	-0.87	-0.89		-8.47	-9.84	-7.59
	(0.55)	(0.56)	(0.58)		(1.71)	(1.89)	(1.72)
$\text{Hisp.}_c \times \text{Guidelines}_t$	0.52	1.09	-0.12		4.91	5.48	4.84
	(0.50)	(0.56)	(0.52)		(1.35)	(1.49)	(1.36)
$\text{Bachelor}_c \times \text{Guidelines}_t$	-0.72	-1.41	-0.50		6.39	5.55	4.94
	(0.78)	(0.82)	(0.83)		(2.19)	(2.66)	(2.19)
Mexican_{ct}		-0.72				-2.89	
		(0.90)				(1.76)	
$\times\text{Guidelines}_t$		-1.70				-1.89	
		(0.87)				(1.51)	
$\text{Central American}_{ct}$		-4.74				-8.39	
		(1.14)				(2.72)	
$\times\text{Guidelines}_t$		0.09				-0.003	
		(1.06)				(2.57)	
Minor				Serious			
$\text{Drug possession}_{ct}$			-1.34	Smuggling_{ct}			8.76
			(2.13)				(2.45)
$\times\text{Guidelines}_t$			-4.46	$\times\text{Guidelines}_t$			-7.41
			(2.16)				(2.49)
$\text{Traffic violation}_{ct}$			0.02	Assault_{ct}			8.72
			(0.95)				(2.36)
$\times\text{Guidelines}_t$			-5.48	$\times\text{Guidelines}_t$			-6.87
			(0.96)				(2.51)
Other_{ct}			-5.04	Other_{ct}			9.41
			(1.11)				(9.05)
$\times\text{Guidelines}_t$			1.29	$\times\text{Guidelines}_t$			-21.30
			(1.09)				(10.16)
R squared	0.02	0.03	0.04		0.04	0.05	0.05
Observations	2,348	2,347	2,347		1,101	1,095	1,095

Table 6: Preference alignment and observable characteristics. The table reports coefficients for county fixed effects models. The dependent variable is log of preference alignment π^{Hh}/π^{Hl}, for minor offenses cases (columns 1-3), and serious offenses cases (columns 4-6). Each observation corresponds to a county-semester. Regressors include: county and semester fixed effects, county characteristics interacted with the policy change and time varying county-specific covariates. Democratic share is an average of the 2008 and 2012 Democratic presidential vote shares minus 50 percent. Bachelor share is measured as the fraction of the adult population with a bachelor's degree or more. Bachelor and Hispanic share are taken from the 2006-2010 waves of the American Communities Survey. Guidelines is a dummy variable indicating the semesters after the guidelines change. Mexican and Central American shares are the fractions of detainers issued against immigrants of those nationalities in the county-semester. All categories of offenses (drug possession, traffic violations, and other for minor, and assaults, smuggling –which includes drug trafficking and smuggling aliens–, and other for serious) are shares of detainers issued against unlawfully present immigrants in the county-semester. For minor offenses, the omitted categories is the share without a criminal conviction or with an immigration violation only. For serious offenses, the omitted category is the share of burglaries. Standard errors are robust to arbitrary heteroskedasticity.

the change in the enforcement guidelines. Within our framework, the policy change manifests itself in two ways: first, changes in preferences over the pool of arrestees (in particular over our measure of preference alignment) reflect changes in ICE removal priorities. Second, federal enforcement efforts may have changed in response to the shock to the policy environment. We study the change in preferences by comparing the periods before and after the guidelines change. We then study the change in federal efforts while holding constant preferences, by simulating a scenario without the guidelines change and comparing it to our baseline model predictions.

6.4.1 Changes in federal preferences over immigration enforcement cases

Our ability to recover measures of the extent of local-federal alignment of preferences for each county-semester, $\pi^{Hh}/\pi^{H\ell}$, allows us to establish how observable characteristics of the pool of arrestees shape the conflict over immigration policy, and how this relationship was altered by the change of focus at the federal level. With this purpose in mind, in Table 6 we estimate county fixed-effects regressions of $\log(\pi^{Hh}/\pi^{H\ell})$ for minor and serious offenses cases on interactions between a post-guidelines dummy and county characteristics, and between a post-guidelines dummy and the composition of the pool of unlawfully present immigrants along key observable case characteristics. Note that in this setting, we can interpret the guidelines dummy as indicating a 'regime change' in the meaning of H, as the unlawfully present immigrants entering the pipeline now reflect a different set of federal-level priorities.

Other than county and semester fixed effects, in columns 1 and 4 we only include key county demographics interacted with the post-guidelines dummy. We find a pattern that remains unaltered in subsequent specifications: after the change in federal guidelines, changes in preference alignment over minor offenses cases (column 1) are on average no different between counties with varying Democratic vote shares, Hispanic population shares, or Bachelor's degree shares. The pattern over serious offenses cases (column 4) is very different. Following the change in federal guidelines, more Democratic counties saw larger decreases in preference alignment compared to more Republican counties. In contrast, counties with larger Hispanic shares saw larger increases in preference alignment compared to counties with smaller Hispanic shares. This last pattern is very similar for counties with more educated populations. Because the federal policy change purported to strengthen immigration enforcement towards serious offenses cases, the relatively larger increase in measured local-federal conflict in more Democratic counties suggests a preference for more leniency over these types of cases in communities with more Democratic voters. In contrast, the relatively larger decrease in measured local-federal conflict in counties with more Hispanics and college graduates suggests a preference for less leniency over serious offenses cases in communities with more Hispanics and college graduates.

In columns 2 and 5 we consider how preferences relate to the composition of cases moving along the immigration enforcement pipeline by national origin.[37] We do this including the share of cases of Mexican nationals and the share of cases of Central American nationals, and their interaction with the post-guidelines dummy.[38] All other nationalities constitute the omitted category. During our period of study, Mexican and Central American nationals constitute the bulk of unlawfully present immigrants (65 and 18 percent of all detainers in our sample period), with the fraction of cases of Central Americans growing over time.

For both minor and serious offenses, larger shares of Central Americans in the pipeline are associated to more conflict (less alignment) between local and federal levels. This pattern remained unaltered after the change in federal guidelines, suggesting i) that the change in focus of the federal level did not lead to substantial changes in the types of Central American unlawfully present immigrants entering the immigration enforcement pipeline, and ii) that Central Americans entering the pipeline had characteristics making them disproportionately unlikely to be perceived as amenable for deportation from the perspective of the average county. In contrast, a larger share of Mexicans in the pipeline for minor offenses is associated with more conflict after the change in federal guidelines but not before. Under the plausible assumption that county-level preferences over unlawfully present immigrant characteristics did not change at the time of the introduction of the new federal guidelines (i.e., that the meaning of h and ℓ did not change systematically with the federal policy change), this pattern reveals that the new federal guidelines shifted the composition of Mexican unlawfully present immigrants convicted of minor offenses towards types less amenable for deportation from the average county's perspective. Quantitatively, a one standard deviation increase in the share of cases of Mexican unlawfully present immigrants convicted of a minor offense is associated with a 0.1 standard deviations increase in log misalignment in the post-guidelines period.[39]

In columns 3 and 6 we then consider how preferences relate to the composition of cases moving along the immigration enforcement pipeline by type of crime. For cases classified as minor, we group them into drug possession charges (5 percent of all cases), traffic violations (17 percent of all cases), no known convictions (60 percent of all cases), and other (18 percent of all cases). This last group includes a large variety of infrequent offenses. Leaving the no known convictions group as the omitted category, in column 3 we include the share of each of the remaining categories of minor offenses and their interaction with the post-guidelines dummy. Following the change in federal guidelines, periods with relatively more drug possession and traffic violation cases are associated with significantly more local-federal conflict. This pattern does not arise before the guidelines changed, indicating that the change in federal priorities led to a recomposition of

[37]Our detainer data also reports the sex of the unlawfully present arrestee. Because more than 95 percent of them are males, we do not include this covariate in the analysis.

[38]Central American nationals include individuals from any of the following countries: Belize, El Salvador, Guatemala, Honduras, Nicaragua, and Panama.

[39]$0.1 = (-1.7 \times 0.23)/3.97$ where 0.23 is one standard deviation of the Mexican share for minor offenses, and 3.97 is one standard deviation of log misalignment for minor offenses.

the characteristics of cases entering the pipeline, making the typical drug possession and traffic violation case less amenable to deportation from the average county's perspective. Conversely, the shift away from federal enforcement over minor offenses under the new guidelines led to a change in the pool of cases entering the pipeline that increased local-federal agreement over the removability of cases involving no conviction. In other words, under the new guidelines, a larger share of immigrants with no conviction perceived as non removable by the local level, became similarly not amenable for removal by ICE (L).

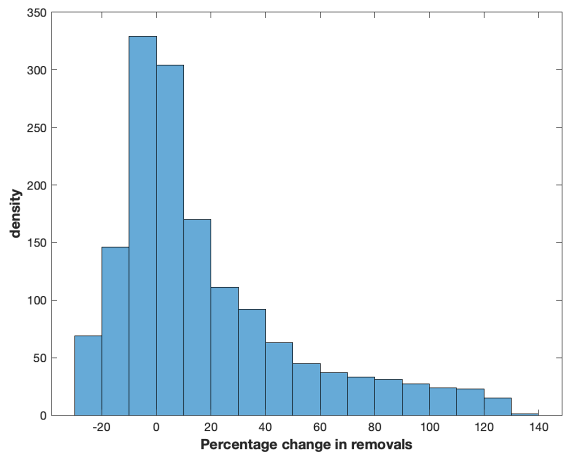
Finally, moving on to column 6 we consider serious offenses, classified into the following categories: smuggling –of aliens or narcotics– (20 percent of cases), assaults (45 percent of cases), burglaries (33 percent of cases), and other (2 percent of cases). Here we leave the share of burglaries as the omitted category. The change in federal guidelines led to very large changes in preference alignment between the federal and local levels. Prior to the change in guidelines, semesters where the pool of cases had relatively more of the most serious ones (smuggling of drugs or aliens and assaults), were associated with increased alignment. Thus, in the typical drug smuggling case for which ICE was pursuing a removal, the county was likely in agreement. A one standard deviation increase in the share of smuggling cases is associated with a 0.16 standard deviations increase in log alignment during the pre-guidelines period.[40] This pattern was almost fully undone with the introduction of the new guidelines, for both smuggling and assault cases. It indicates that the new federal focus on serious offenses led to a large recomposition of the types of serious cases reaching the pipeline, towards smuggling and assault cases with characteristics much less amenable for deportation from the average county's perspective.

6.4.2 Counterfactual exercise: No change in the federal guidelines

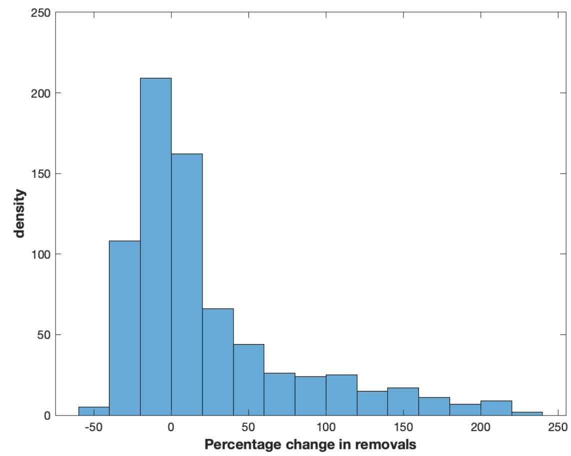
Besides a change in preferences, the 2011 guidelines also changed how the federal level targeted its enforcement efforts. Within our framework, this is manifested as a change in the underlying relationship between the composition of the pool, $\pi^{Hh}/\pi^{H\ell}$, and federal efforts, ξ, in the post-guidelines period. Our approach does not allow us to make direct welfare comparisons. It does allows us, however, to assess the effects of the guidelines by considering a counterfactual scenario *in their absence*. We can then compare the evolution of immigration enforcement outcomes under this counterfactual exercise to the predictions from our model estimates.

Thus, we take the recovered relationship between federal efforts and alignment across counties in the pre-guidelines period regressing ξ_{ct} on $\log(\pi^{Hh}/\pi^{H\ell})_{ct}$ (see Figure 5), and use it to predict the federal enforcement efforts $\hat{\xi}_{ct}$ that would have occurred post-guidelines *at the actual* $(\pi^{Hh}/\pi^{H\ell})_{ct}$'s, under the pre-guidelines regime. In this way we hold selection constant. With these counterfactual federal efforts for the post-guidelines period we then use the best responses for each

[40] $0.16 = (8.76 \times 0.14)/7.52$ where 0.14 is one standard deviation of the Smuggling share of serious offenses, and 7.52 is one standard deviation of log misalignment for serious offenses.



(a) Minor offenses



(b) Serious offenses

Figure 6: Distribution of Percent Changes in Removals: No Change in Guidelines Counterfactual vs. Baseline Prediction. Panel (a) shows a histogram of the distribution across county-time periods of percent changes in removals for minor (levels 2-4) offenses, between the no change in guidelines counterfactual and the baseline prediction based on the model estimates. Panel (b) shows a histogram of the distribution across county-time periods of percent changes in removals for serious (level 1) offenses, between the no change in guidelines counterfactual and the baseline prediction based on the model estimates.

county to predict the counterfactual local enforcement efforts $\hat{\epsilon}_{ct}$ that would have been observed in response to these federal efforts.[41] Armed with these $\hat{\epsilon}_{ct}$'s and $\hat{\xi}_{ct}$'s, and using our parameter estimates, we recover the implied counterfactual enforcement probabilities $\{\hat{f}, \hat{g}, \hat{k}, \hat{q}^h, \hat{q}^\ell\}_{ct}$. Finally, combining the preference alignments with these counterfactual enforcement probabilities, we recover the counterfactual immigration enforcement outcomes $\mathbb{P}$(ICE Custody|Detainer), $\mathbb{P}$(Removal|ICE Custody, Detainer), and $\mathbb{P}$(Removal|ICE Custody, No Detainer) using equations (3), (4), and (12).[42] Figure B.6 compares graphically the time evolution (predicted and counterfactual) of each immigration enforcement outcome, which Appendix A.4 discusses in detail.

We compute the counterfactual percent difference in number of deportations relative to the baseline prediction for each county-time period following the change in guidelines. As we show in Appendix A.3, this quantity is identified. This exercise holds constant the composition of the pool of arrested unlawfully present immigrants. Thus, it is informative about the impact of the change in federal guidelines that can be attributed to the endogenous response of the local level and the subsequent screening effects taking place down the pipeline. Figure 6 plots the resulting distributions of percent differences for minor and serious offenses cases, across county-time periods after 2011-II. Recall that the change in guidelines purported to relax enforcement towards minor offenses cases, and redirect it towards serious offenses cases. In the absence of such a policy change, but holding fixed any effects the policy may have had over the composition of

[41] Notice that while the first step where we obtain counterfactual $\hat{\xi}_{ct}$'s based on $(\pi^{Hh}/\pi^{H\ell})_{ct}$ is purely predictive, the second step that recovers counterfactual $\hat{\epsilon}_{ct}$'s based on $\hat{\xi}_{ct}$'s is causal.

[42] We cannot recover the baseline rates $\mathbb{P}$(Detainer|Arrest) or $\mathbb{P}$(ICE Custody|No Detainer) from equations (2) and (11) of each track because we only observe $\pi^{Hh}/\pi^{H\ell}$ but not π^{Hh} and $\pi^{H\ell}$ separately.

the arrest pool, the median county-semester would have experienced 5.8 and 3.2 percent more removals for minor and serious offenses cases. There is ample variation across county-time periods in the outcomes of this comparison, however.[43] Across county-semesters, more than 60 percent would have experienced strictly more removals in the absence of the federal guidelines change. A quarter of county-semesters would have observed removals to be more than 50 percent higher. Thus, holding fixed federal-level preferences over removal priorities, the countervailing response of the local level would not have been enough to reduce removals if the federal level had kept the direction of its enforcement efforts unchanged.

Using the observed distribution of offenses observed, we can additionally compute the aggregate (over all county-time periods) percent difference in removals under this counterfactual exercise, by type of offense across all counties and semesters following the policy change. We estimate 18 percent more counterfactual deportations related to minor offenses, with little differences across categories (no conviction, immigration violation, drug possession, traffic offense). In contrast, we estimate 104 percent more counterfactual deportations related to serious offenses, in the absence of the change in guidelines. Thus, holding selection constant, we can attribute to the policy change a 15 percent reduction in deportations for minor offenses and a 50 percent reduction in deportations for serious offenses over the subsequent three and a half years. We also find considerable variation across types of offenses: using the counterfactual, we can attribute to the guidelines a 44 percent reduction in deportations for smuggling and burglary cases, a 60 percent reduction in deportations for drug trafficking cases, and a 78 percent reduction in deportations for assault cases. These numbers reflect the reduced local opposition to federal efforts aimed at more serious offenses, especially for drug trafficking and assault cases.

6.5 The Immigration Courts

Immigration courts constitute the last step of the immigration enforcement pipeline. They are the instance making actual deportation decisions and as such, play an outsized role in the process. Through a series of counterfactual exercises, we explore here how institutional changes at the immigration court level would impact immigration enforcement outcomes.

6.5.1 Secession from the executive branch

As we pointed out earlier, immigration courts in the US are under the jurisdiction of the Department of Justice, and as such, are part of the federal executive branch. This motivated us to allow in our model of the immigration enforcement pipeline, a dependence between federal enforcement efforts and the conditional probabilities of removal at the court stage: in equation (20), γ^τ indicates how, on average, courts change the likelihood of removing type $\tau \in \{\ell, h\}$ unlawfully present

[43] Mean percent differences between counterfactual and predicted removals are 47 and 150 percent for minor and serious cases.

	Minor Offenses			Serious Offenses		
	Median	Positive change	Aggregate	Median	Positive change	Aggregate
Courts secede	1.1%	60.4%	0.6%	2.9%	67.2%	5.1%
Courts severity homogenized						
10th percentile	-47.5%	3.8%	-39.2%	-31.7%	6.0%	-24.6%
50th percentile	1.2%	52.3%	1.2%	1.8%	52.7%	3.0%
90th percentile	33.1%	93.8%	28.2%	32.5%	91.4%	28.8%
Observations	2,347	2,347	2,347	1,095	1,095	1,095

Table 7: Percent change in removals under immigration court-related counterfactuals. The table reports the changes in removals between several court-related counterfactual scenarios and the baseline prediction based on the model estimates following the description in appendix A.3. Median refers to the median percentage change in removals across all county-periods. Positive change refers to fraction of county-periods for which counterfactual removals are higher than actual removals. Aggregate refers to overall percentage changes in removals across all county-periods between the counterfactual and the baseline prediction based on the model estimates.

immigrants as the federal level's enforcement effort ξ_{ct} varies, holding constant the composition of the pool of unlawfully present immigrants entering the pipeline. How does the dependence between immigration court behavior and federal enforcement efforts shape immigration outcomes? A way to answer such question is to consider a hypothetical policy reform that makes the courts no longer be under the jurisdiction of the executive, which, in the context of our model, we impose by setting $\gamma^{\tau} = 0$. Of course, this is a 'partial equilibrium' counterfactual as it supposes that neither ICE nor the counties alter their behavior in response to the institutional change.

Similar to the counterfactual exercise above, we can simulate the percent difference in removals between the counterfactual scenario and the baseline model predictions for each county semester. We present the main results of this exercise in Table 7 under the row labeled 'Courts secede'. Note that our estimates of γ^{ℓ} are positive, while our estimates of γ^{h} are negative (see Table 2) for both minor and serious offenses. On average courts reinforced ICE efforts when the pool contained more ℓ types, and counteracted ICE efforts when the pool contained more h types. Thus, the change in removals under the counterfactual in a given county-semester could be positive or negative depending on the federal efforts we recovered. Figure B.7 plots the full distribution of counterfactual percent changes. Across the distribution of county-semesters, 60 percent would observe higher removals of minor offenses cases under seceded courts that under the baseline. The median county-semester would experience a 1.1 percent higher number of removals. Aggregating over all county-semesters, seceded courts would lead to only a 0.6 percent higher number of removals. Looking at serious offenses cases, 67 percent of county-semesters would observe higher removals under seceded courts that under the baseline. The median county-semester would experience a 2.9 percent higher number of removals. Finally, aggregating over all county-semesters, seceded courts would lead to a 5 percent higher number of removals. Fully independent immigration courts, on aggregate, would have increased the harshness of the deportation process, particularly for serious offenses. This general pattern hides interesting dynamics: it is driven by the semesters after the change in federal policy guidelines, during which we know ICE became more lenient.

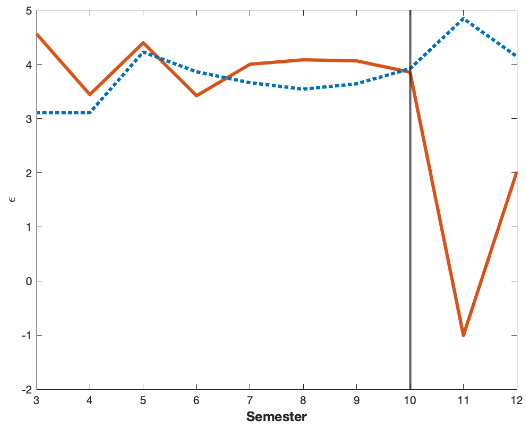
We can additionally recover counterfactual changes conditional on observable case characteristics: type of offense, and some demographics. We report the full set of these numbers in Table B.7. Among types of minor offenses, removals of cases involving traffic violations would be 1.3 percent higher on aggregate under the independent courts. Cases involving no know conviction, in contrast, would barely change. Among types of serious offenses, removals of burglary cases would increase by 5.3 percent, while those involving assaults would increase by 2.1 percent, suggesting that assaults are a priority for ICE. Looking at demographics, removals of Central American nationals would increase by 6 percent, while removals of Mexican nationals would increase only by 4 percent suggesting that the removal of Mexican nationals was a priority for ICE.

6.5.2 Homogenization of immigration court severity

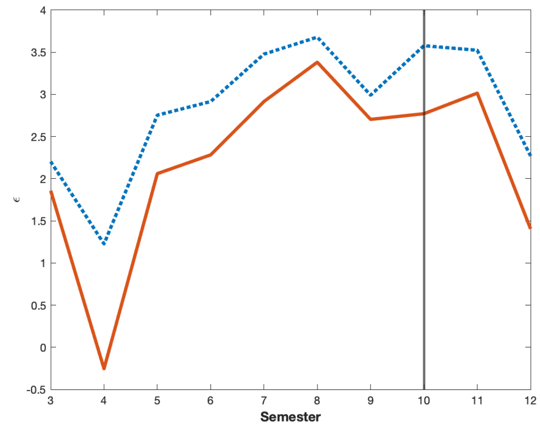
Another consideration of interest in the context of court proceedings is arbitrariness: different courts making dissimilar decisions on (observably) similar cases. Conditional on county characteristics $\mathbf{x}_c$ and federal enforcement efforts ξ_{ct}, in our model the residual variation in removals of type $\tau \in \{\ell, h\}$ unlawfully present immigrants at the court stage is captured by ζ_{ct}^{τ}, the residuals from equation (20).

How would the distribution of removals across county-semesters change if, conditional on observables, all immigration courts were equally harsh? We provide a partial answer to that question here with a counterfactual exercise where we use the distribution of estimated ζ_{ct}^{τ}'s recovered from our model estimates, to simulate the resulting percent difference in removals between the counterfactual and the baseline model predictions by assigning to every county-semester the same value of ζ_{ct}^{τ}. In particular, we explore three possibilities: i) very lenient courts, where we use the 10th percentile of the distribution of ζ_{ct}^{τ}; ii) median-leniency courts, where we use the 50th percentile of the distribution of ζ_{ct}^{τ}; and iii) harsh courts, where we use the 90th percentile of the distribution of ζ_{ct}^{τ}.

The main results of these exercises appear in Table 7 on the rows under the label 'Courts severity homogenized'. The corresponding distributions of percent changes appear in Figure B.8, and additional results by case characteristics appear in Table B.7. The aggregate number of removals for minor offenses across all counties and time periods would be 39 percent lower if we moved all courts to the 10th percentile of the distribution of ζ_{ct}^{τ}. They would be 1.2 percent higher if all courts were at the median, and they would be 28 percent higher if we moved all courts to the 90th percentile. The pattern is similar for serious offenses, albeit somewhat less elastic: here removals would be 25 percent lower at the 10th percentile, 3 percent higher at the median, and 28.8 percent higher at the 90th percentile. Under the extreme leniency counterfactual, aggregate percent falls in removals would be larger for cases involving minor offenses such as drug possession and traffic violations (around 40 percent reductions), while removals of cases involving serious offenses such as drug smuggling and assault would fall by 18 to 25 percent (see Table B.7). This



(a) Minor offenses



(b) Serious offenses

Figure 7: Evolution of Local immigration enforcement efforts and the California Trust Act. The figure plots the evolution over time of the median of the estimated local immigration enforcement efforts ϵ across counties. The red line depicts the median for California counties. The blue line depicts the median for all other US counties. The vertical black line represents the semester of implementation of the Trust Act. Panel a reports the medians for minor offenses cases. Panel b reports the medians for serious offenses cases. The number of California counties is 30 for minor offenses and 24 for serious offenses. The number of non-California counties is 447 for minor offenses and 199 for serious offenses.

suggests that courts exercise more discretion on relatively less serious cases.

Naturally, collapsing all of the idiosyncratic variation in court behavior to a mass point is not feasible (and possibly not desirable). However, because the estimated changes we describe here hold constant the composition of the pool of cases in the pipeline, the exercise highlights that policies intended to reduce exclusively the idiosyncratic component of immigration court decision-making (e.g., mandatory minimums, sentencing guidelines, a stronger dependence of the courts on the executive, etc.) can have a considerable impact on deportation rates. The exit door of the pipeline appears to play a key role in explaining the pattern of deportations under the Secure Communities program.

6.6 Model Validation: The California Trust Act

We conclude with a validation exercise for our model, based on California's Trust Act. This law passed in 2013 and came into effect on January 2014. It imposed stringent limits on local-level collaboration with detainer requests from ICE. Under the Trust Act, local police are only allowed to honor detainers falling into a specific list of relatively serious offenses.[44] Our model does not account for the passage of the Trust Act, giving us an opportunity to assess whether our estimates of local immigration enforcement efforts do capture the patterns we expected to have taken place under this law. Figure 7 presents the evolution over time of the median of our estimated local immigration enforcement efforts $\hat{\epsilon}_{ct}$, distinguishing between California counties (in red) and all

[44] For a detailed description of the Trust Act and the list of offenses for which the county officials are allowed to cooperate with ICE, see California (2014).

other counties (in blue). The vertical line indicates the activation of the Trust Act. In panel a we see that local efforts over minor offenses cases fall sharply for California counties at the time of the policy change. The Trust Act allowed local law enforcement to collaborate with ICE for the most serious offenses cases, however. Consistent with our expectations, panel b shows that for serious offenses cases, California counties experienced a decline in local effort not dissimilar to what happened in the rest of the US. We see these results as validating the ability of our model to capture accurately the patterns of immigration enforcement under Secure Communities.

7 Concluding Remarks

We study immigration enforcement under the Secure Communities program, as a window into conflict over policy under federalism. We emphasize the importance of the strategic interaction between local and federal levels, and propose a framework to disentangle the roles of selection, local, and federal enforcement efforts, as drivers of the variation in immigration enforcement outcomes. We do this by exploiting the institutional details of the immigration enforcement process. Our strategy relies on rich data from the Secure Communities program, describing the pipeline taking unlawfully present immigrants arrested by local law enforcement into ICE custody and eventually deportation. We find strong evidence of strategic substitutabilities in the response of the local level (county) to changes in federal-level immigration enforcement, particularly among the most Democratic counties. We also find that ICE is very effective at directing its enforcement efforts towards counties where it can expect local collaboration (possibly because of the considerable informational advantage it acquired under Secure Communities). Finally, estimating a series of counterfactual exercises we quantify the impact of the 2011 federal policy change as well as the role of the courts on the number and composition of removals. The impact of the policy was highly heterogenous, underlying the importance of local preferences in shaping immigration enforcement outcomes. We also show that reducing discretion at the immigration court stage, and removing the executive power's jurisdiction over the immigration courts, would have a significant impact on removals. Subsequent research should be directed at understanding the drivers of federal-level preferences over immigration outcomes.

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A Online Appendix A

A.1 Proof of Proposition 1

Given a vector of observables $\mathbf{w} = (x_1, x_2, x_3, y_1, y_2)$, where $x_1 > x_2 > x_3 > 0$ and $y_1 > y_2 > 0$, the following is the exhaustive list of constraints on observed probabilities:

$$
\begin{array}{cccc}
0 < g < 1 & 0 < f < 1 & 0 < q^\ell < 1 & 0 < q^h < 1 \\
0 < k < 1 & 0 < v^d < 1 & 0 < \pi^{H\ell} < 1 & 0 < \pi^{Hh} < 1
\end{array}
$$

The immigration enforcement process also implies:

$$g = \frac{x_3 - x_2 q^h}{x_3 - x_2 q^\ell - x_1(q^h - q^\ell)} \tag{A.1}$$

$$k = \frac{(x_2 - x_1 g)(y_1 q^h - y_2)}{(x_1 - x_2)(y_2 - y_1 q^\ell)} \tag{A.2}$$

$$v^d \left(\frac{1-f}{f}\right) = \frac{(1-x_1)(1-g)}{x_2 - x_1 g} \frac{y_2 - y_1 q^\ell}{q^h - q^\ell} \tag{A.3}$$

Beginning with $g > 0$, from equation (A.1) we have two possible cases:
Case Ia:

$$x_3 - x_2 q^h > 0 \text{ and } x_3 - x_2 q^\ell - x_1(q^h - q^\ell) > 0, \text{ or}$$

Case Ib:

$$x_3 - x_2 q^h < 0 \text{ and } x_3 - x_2 q^\ell - x_1(q^h - q^\ell) < 0.$$

Under Case Ia,

$$q^h < \frac{x_3}{x_2} \text{ and } q^\ell > \frac{x_3}{x_2 - x_1} + \frac{x_1}{x_1 - x_2} q^h$$

Under Case Ib,

$$q^h > \frac{x_3}{x_2} \text{ and } q^\ell < \frac{x_3}{x_2 - x_1} + \frac{x_1}{x_1 - x_2} q^h$$

From $g < 1$, equation(A.1) implies two possible cases:
Case IIa:

$$q^h < \frac{x_3}{x_2} \text{ and } q^\ell > \frac{x_3}{x_2 - x_1} + \frac{x_1}{x_1 - x_2} q^h \text{ and } q^h < q^\ell, \text{ or}$$

Case IIb:

$$q^\ell < \frac{x_3}{x_2 - x_1} + \frac{x_1}{x_1 - x_2} q^h \text{ and } q^h > q^\ell$$

Now we turn to $k > 0$ which, together with equation (A.2) yields four possible cases:
Case IIIa:

$$x_2 - x_1 g > 0 \text{ and } y_1 q^h - y_2 > 0 \text{ and } y_2 - y_1 q^\ell > 0, \text{ or}$$

Case IIIb:

$$x_2 - x_1 g > 0 \text{ and } y_1 q^h - y_2 < 0 \text{ and } y_2 - y_1 q^\ell < 0, \text{ or}$$

Case IIIc:

$$x_2 - x_1 g < 0 \text{ and } y_1 q^h - y_2 < 0 \text{ and } y_2 - y_1 q^\ell > 0, \text{ or}$$

Case Illd:

$$x_2 - x_1 g < 0 \text{ and } y_1 q^h - y_2 > 0 \text{ and } y_2 - y_1 q^\ell < 0.$$

Under Case IIIa,

$$g < \frac{x_2}{x_1} \text{ and } q^h > \frac{y_2}{y_1} \text{ and } q^\ell < \frac{y_2}{y_1}$$

Under Case IIIb,

$$g < \frac{x_2}{x_1} \text{ and } q^h < \frac{y_2}{y_1} \text{ and } q^\ell > \frac{y_2}{y_1}$$

Under Case IIIc,

$$g > \frac{x_2}{x_1} \text{ and } q^h < \frac{y_2}{y_1} \text{ and } q^\ell < \frac{y_2}{y_1}$$

Under Case IIId,

$$g > \frac{x_2}{x_1} \text{ and } q^h > \frac{y_2}{y_1} \text{ and } q^\ell > \frac{y_2}{y_1}$$

From $k < 1$ together with equation (A.2), we have four cases:
Case IVa: Same constraints as in Case IIIa, which imply

$$g > \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1}\frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}$$

where the second term in the right-hand side is positive.
Case IVb: Same constraints as in Case IIIb, which imply

$$g > \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1}\frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}$$

where the second term in the right-hand side is positive.
Case IVc: Same constraints as in Case IIIc, which imply

$$g < \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1}\frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}$$

where the second term in the right-hand side is negative.
Case IVd: Same constraints as in Case IIId, which imply

$$g < \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1}\frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}$$

where the second term in the right-hand side is negative.
Now we turn to equation (A.3). Together with $0 < f < 1$ and $0 < v^d < 1$, it implies four possible cases:
Case Va:

$$g < \frac{x_2}{x_1} \text{ and } q^\ell < \frac{y_2}{y_1} \text{ and } q^h > q^\ell, \text{ or}$$

Case Vb:

$$g < \frac{x_2}{x_1} \text{ and } q^\ell > \frac{y_2}{y_1} \text{ and } q^h < q^\ell, \text{ or}$$

Case Vc:

$$g > \frac{x_2}{x_1} \text{ and } q^\ell > \frac{y_2}{y_1} \text{ and } q^h > q^\ell, \text{ or}$$

Case Vd:

$$g > \frac{x_2}{x_1} \text{ and } q^\ell < \frac{y_2}{y_1} \text{ and } q^h < q^\ell.$$

Collecting cases II, IV, and V, we have four possible regions in (q^h, q^ℓ) space with corresponding ranges for g:
Region I:

$$I = \left\{(q^h, q^\ell, g) : q^h \in \left[0, \frac{y_2}{y_1}\right], q^\ell \in \left[\frac{y_2}{y_1}, 1\right], g \in \left(\frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1}\frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}, \frac{x_2}{x_1}\right)\right\}$$

Region II:

$$II = \left\{(q^h, q^\ell, g) : q^h \in \left[\frac{y_2}{y_1}, 1\right], q^\ell \in \left[\frac{y_2}{y_1}, 1\right], q^h > q^\ell, g \in \left(\frac{x_2}{x_1}, \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1}\frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}\right)\right\}$$

Region III:

$$III = \left\{ (q^h, q^\ell, g) : q^h \in \left[0, \frac{y_2}{y_1}\right], q^\ell \in \left[0, \frac{y_2}{y_1}\right], q^h < q^\ell, g \in \left(\frac{x_2}{x_1}, \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1} \frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2} \right) \right\}$$

Region IV:

$$IV = \left\{ (q^h, q^\ell, g) : q^h \in \left[\frac{y_2}{y_1}, 1\right], q^\ell \in \left[0, \frac{y_2}{y_1}\right], g \in \left(\frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1} \frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}, \frac{x_2}{x_1} \right) \right\}$$

Now we can turn to $0 < \pi^{H\ell} < 1$ and $0 < \pi^{Hh} < 1$. Together these imply that $\pi^{Hh}/\pi^{H\ell} > 0$. From equation (8), it follows that

$$g < \frac{x_2}{x_1}$$

This rules out regions II and III.

From equation (9), we have two cases:

Case VIa:

$$q^\ell < \frac{x_3}{x_2} \text{ and } q^h > \frac{x_3}{x_2}, \text{ or}$$

Case VIb:

$$q^\ell > \frac{x_3}{x_2} \text{ and } q^h < \frac{x_3}{x_2}, \text{ or}$$

From equation (8), we have that

$$\frac{\pi^{Hh}}{\pi^{H\ell}} = \frac{y_1 q^\ell - y_2}{y_2 - y_1 q^h} k$$

which gives two other cases:

Case VIIa:

$$q^\ell > \frac{y_2}{y_1} \text{ and } q^h < \frac{y_2}{y_1}, \text{ or}$$

Case VIIb:

$$q^\ell < \frac{y_2}{y_1} \text{ and } q^h > \frac{y_2}{y_1}, \text{ or}$$

Collecting cases VI and VII together, we have two regions for (q^h, q^ℓ):

Region R1:

$$R_1 = \left\{ (q^h, q^\ell) : q^h < \min\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1} \right\}, \text{ and } q^\ell > \max\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1} \right\} \right\}$$

Region R2:

$$R_2 = \left\{ (q^h, q^\ell) : q^h > \max\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1} \right\}, \text{ and } q^\ell < \min\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1} \right\} \right\}$$

Notice that the constraints from Cases I and II become redundant relative to the regions defined by R_1 and R_2.

Since we have ruled out regions II and III, it follows that $g > \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1} \frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}$. From equation (A.1), and $g > 0$, we have that if $q^h < \frac{x_3}{x_2}$, then $x_3 - x_2 q^\ell - x_1(q^h - q^\ell) > 0$. In this case, after some algebra it follows that g attains this lower bound for any

$$q^\ell > \frac{x_1 y_2 - x_3 y_1}{y_1(x_1 - x_2)}.$$

Similarly, if $q^h > \frac{x_3}{x_2}$, then $x_3 - x_2 q^\ell - x_1(q^h - q^\ell) < 0$, in which case g attains this lower bound for any

$$q^\ell < \frac{x_1 y_2 - x_3 y_1}{y_1(x_1 - x_2)}.$$

This, together with R_1 and R_2 gives us

$$\mathcal{R}_1 = \left\{ (q^h, q^\ell) : q^h < \min\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1} \right\}, \text{ and } q^\ell > \max\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1}, \frac{x_1 y_2 - x_3 y_1}{y_1(x_1 - x_2)} \right\} \right\}$$

and

$$\mathcal{R}_2 = \left\{ (q^h, q^\ell) : q^h > \max\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1} \right\}, \text{ and } q^\ell < \min\left\{ \frac{x_3}{x_2}, \frac{y_2}{y_1}, \frac{x_1 y_2 - x_3 y_1}{y_1(x_1 - x_2)} \right\} \right\}$$

so the identified set for (q^h, q^ℓ) is given by $\mathcal{R} = \mathcal{R}_1 \cup \mathcal{R}_2$. Notice that for any $(q^h, q^\ell) \in \mathcal{R}$, the implied values for g and k are always valid probabilities, and $v^d(1-f)/f > 0$, and $g > \frac{x_2}{x_1} - \frac{x_1 - x_2}{x_1} \frac{y_2 - y_1 q^\ell}{y_1 q^h - y_2}$.

A.2 Inference for the coefficients in equations (19) and (20)

In equations (19) and (20), ϵ_{ct} and ξ_{ct} are generated regressors because these residuals are recovered using not the true $(\boldsymbol{\delta}^d, \boldsymbol{\beta}^f, \boldsymbol{\beta}^g)$ coefficients from equations (17) and (18), but *estimates* of these coefficients. Thus, we must account for the sampling variation induced by our use of estimates of ϵ_{ct} and ξ_{ct} on the variance of the estimator for $(\boldsymbol{\beta}^k, \kappa_\epsilon, \kappa_\xi, \boldsymbol{\beta}^{q\tau}, \gamma^\tau)$. Our derivation closely follows (Wooldrige, 2002, p. 139-141). We present below the derivation of the variance-covariance matrix for the OLS estimator of the coefficients in equation (19) only. The corresponding derivation for the OLS estimator of the coefficients in equation (20) is analogous, only simpler because while equation (19) has two generated regressors, equation (20) only has one generated regressor. Consider the log-odds equation

$$\tilde{k}_{ct} = \mathbf{x}_c \boldsymbol{\beta}^k + \kappa_\epsilon \epsilon_{ct} + \kappa_\xi \xi_{ct} + \eta_{ct} \tag{A.4}$$

with $dim(\mathbf{x}_c) = K$, and re-write it as

$$\tilde{k}_{ct} = \mathbf{x}_c^* \boldsymbol{\beta} + \eta_{ct}$$

where $\mathbf{x}_c^* \equiv [\mathbf{x}_c, \xi_{ct}, \epsilon_{ct}]$, and $\boldsymbol{\beta} \equiv [\boldsymbol{\beta}^{k'}, \kappa_\xi, \kappa_\epsilon]'$. Using equations (18) and (21), we can now notice that $\mathbf{x}_c^* = \mathcal{F}(\mathbf{z}_{ct}, \boldsymbol{\delta})$, where

$$\mathcal{F}(\mathbf{z}_{ct}, \boldsymbol{\delta}) = \mathbf{z}_{ct} \Delta(\boldsymbol{\delta}),$$

where $\boldsymbol{\delta} \equiv [\boldsymbol{\delta}^{d'}, -\boldsymbol{\beta}^{f'}, -\boldsymbol{\beta}^{g'}]$, $\mathbf{z}_{ct} \equiv [\mathbf{x}_c, v_{ct}^d, \bar{\tilde{f}}, \tilde{g}]$, $v_{ct}^d \equiv (0, ...1..., 0)$ is a vector of dimensions $1 \times D$ where D is the number of federal districts minus one that has a 1 in the column corresponding to the district that county c belongs to, and

$$\Delta(\boldsymbol{\delta}) \equiv \begin{bmatrix} \mathbf{I}_{K \times K} & -\boldsymbol{\beta}^f & -\boldsymbol{\beta}^g \\ \mathbf{0}_{D \times 1} & \boldsymbol{\delta}^d & \mathbf{0}_{D \times 1} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Define T_c as the number of time periods available for county c, and thus $N \equiv \sum_c T_c$ as the total number of observations. We have a $\sqrt{N}$ consistent estimator of $\boldsymbol{\delta}$, namely $\hat{\boldsymbol{\delta}} = [\hat{\boldsymbol{\delta}}_{OLS}^{d'}, -\hat{\boldsymbol{\beta}}_{OLS}^{f'}, -\hat{\boldsymbol{\beta}}_{OLS}^{g'}]$, where

$$\begin{bmatrix} \hat{\boldsymbol{\delta}}_{OLS}^d \\ \hat{\boldsymbol{\beta}}_{OLS}^f \end{bmatrix} = \left(\sum \mathbf{x}_c^{F'} \mathbf{x}_c^F \right)^{-1} \left(\sum \mathbf{x}_c^{F'} \bar{\tilde{f}}_{ct} \right), \qquad \mathbf{x}_c^{F'} \equiv [v_{ct}^d, \mathbf{x}_c],$$

and

$$\hat{\boldsymbol{\beta}}_{OLS}^g = \left(\sum \mathbf{x}_c' \mathbf{x}_c \right)^{-1} \left(\sum \mathbf{x}_c' \tilde{g}_{ct} \right).$$

We do not observe the $\mathbf{x}_c^*$ because we do not observe $\boldsymbol{\delta}$. However, we have a consistent estimate of $\boldsymbol{\delta}$, namely $\hat{\boldsymbol{\delta}}$, so we can compute

$$\hat{\mathbf{x}}_c^* = \mathcal{F}(\mathbf{z}_{ct}, \hat{\boldsymbol{\delta}}).$$

It is these $\hat{\mathbf{x}}_c^*$ we use to estimate $\boldsymbol{\beta}$ in the regression equation for $\tilde{k}_{ct}$. Our OLS estimator for $\boldsymbol{\beta}$ is

$$\hat{\boldsymbol{\beta}} = \left(\sum \hat{\mathbf{x}}_c^{*'} \hat{\mathbf{x}}_c^* \right)^{-1} \left(\sum \hat{\mathbf{x}}_c^{*'} \tilde{k}_{ct} \right)$$

We can re-write equation (A.4) as

$$\tilde{k}_{ct} = \hat{\mathbf{x}}_c^* \boldsymbol{\beta} + (\mathbf{x}_c^* - \hat{\mathbf{x}}_c^*) \boldsymbol{\beta} + \eta_{ct}$$

and replace it above to obtain

$$\hat{\boldsymbol{\beta}} = \boldsymbol{\beta} + \left(\sum \hat{\mathbf{x}}_c^{*'} \hat{\mathbf{x}}_c^* \right)^{-1} \left(\sum \hat{\mathbf{x}}_c^{*'} (\mathbf{x}_c^* - \hat{\mathbf{x}}_c^*) \boldsymbol{\beta} + \sum \hat{\mathbf{x}}_c^{*'} \eta_{ct} \right)$$

Thus,

$$\sqrt{N}(\hat{\boldsymbol{\beta}}-\boldsymbol{\beta})=\left(N^{-1}\sum\hat{\mathbf{x}}_c^{*'}\hat{\mathbf{x}}_c^{*}\right)^{-1}\left(N^{-1/2}\sum\hat{\mathbf{x}}_c^{*'}(\mathbf{x}_c^{*}-\hat{\mathbf{x}}_c^{*})\boldsymbol{\beta}+N^{-1/2}\sum\hat{\mathbf{x}}_c^{*'}\eta_{ct}\right)$$

Notice that

$$\hat{\mathbf{C}}\equiv N^{-1}\sum\hat{\mathbf{x}}_c^{*'}\hat{\mathbf{x}}_c^{*}\to^p\mathbb{E}[\hat{\mathbf{x}}_c^{*'}\hat{\mathbf{x}}_c^{*}]$$

and

$$N^{-1/2}\sum\hat{\mathbf{x}}_c^{*'}\eta_{ct}=N^{-1/2}\sum\mathbf{x}_c^{*'}\eta_{ct}+o_p(1)$$

The remaining term can be expressed as

$$N^{-1/2}\sum\hat{\mathbf{x}}_c^{*'}(\mathbf{x}_c^{*}-\hat{\mathbf{x}}_c^{*})\boldsymbol{\beta}=-\left[N^{-1}\sum(\boldsymbol{\beta}\otimes\mathbf{x}_c^{*})'\nabla_\delta\mathcal{F}(\mathbf{z}_{ct},\boldsymbol{\delta})\right]\sqrt{N}(\hat{\boldsymbol{\delta}}-\boldsymbol{\delta})+o_p(1)$$

Defining $\mathbf{G}\equiv\mathbb{E}[(\boldsymbol{\beta}\otimes\mathbf{x}_c^{*})'\nabla_\delta\mathcal{F}(\mathbf{z}_{ct},\boldsymbol{\delta})]$, we have that

$$N^{-1/2}\sum\hat{\mathbf{x}}_c^{*'}(\mathbf{x}_c^{*}-\hat{\mathbf{x}}_c^{*})\boldsymbol{\beta}=-\mathbf{G}\sqrt{N}(\hat{\boldsymbol{\delta}}-\boldsymbol{\delta})+o_p(1)$$

Finally, the term $\sqrt{N}(\hat{\boldsymbol{\delta}}-\boldsymbol{\delta})$ can be expressed as

$$\sqrt{N}(\hat{\boldsymbol{\delta}}-\boldsymbol{\delta})=\sqrt{N}\left(\begin{bmatrix}\hat{\boldsymbol{\delta}}^d_{OLS}\\\hat{\boldsymbol{\beta}}^f_{OLS}\\\hat{\boldsymbol{\beta}}^g_{OLS}\end{bmatrix}-\begin{bmatrix}\boldsymbol{\delta}^d\\\boldsymbol{\beta}^f\\\boldsymbol{\beta}^g\end{bmatrix}\right)=N^{-1/2}\begin{bmatrix}\mathbf{A}_f^{-1} & \mathbf{0}_{(D+K)\times K}\\\mathbf{0}_{K\times(D+K)} & \mathbf{A}_g^{-1}\end{bmatrix}\sum\begin{bmatrix}-\mathbf{x}_{ct}^{F'}\xi_{ct}\\\mathbf{x}_{ct}'\epsilon_{ct}\end{bmatrix}+o_p(1)$$

where $\mathbf{A}_f\equiv(N^{-1}\sum\mathbf{x}_{ct}^{F'}\mathbf{x}_{ct}^{F})$ and $\mathbf{A}_g\equiv(N^{-1}\sum\mathbf{x}_{ct}\mathbf{x}_{ct})$. Thus, we can define

$$\mathbf{r}_{ct}(\boldsymbol{\delta})\equiv\begin{bmatrix}\mathbf{A}_f^{-1} & \mathbf{0}_{(D+K)\times K}\\\mathbf{0}_{K\times(D+K)} & \mathbf{A}_g^{-1}\end{bmatrix}\begin{bmatrix}-\mathbf{x}_{ct}^{F'}\xi_{ct}\\\mathbf{x}_{ct}'\epsilon_{ct}\end{bmatrix}$$

and hence

$$\sqrt{N}(\hat{\boldsymbol{\beta}}-\boldsymbol{\beta})=C^{-1}\left\{N^{-1/2}\sum\left[\mathbf{x}_{ct}^{*'}\eta_{ct}-\mathbf{G}\mathbf{r}_{ct}(\boldsymbol{\delta})\right]\right\}+o_p(1)$$

The Central Limit Theorem implies that

$$\sqrt{N}(\hat{\boldsymbol{\beta}}-\boldsymbol{\beta})\sim\mathcal{N}\left(\mathbf{0},\mathbf{C}^{-1}\mathbf{M}\mathbf{C}^{-1}\right)$$

where $\mathbf{M}\equiv\mathrm{Var}(\mathbf{x}_{ct}^{*'}\eta_{ct}-\mathbf{G}\mathbf{r}_{ct}(\boldsymbol{\delta}))$. A consistent estimator for this asymptotic variance is given by $(\hat{\mathbf{C}}^{-1}\hat{\mathbf{M}}\hat{\mathbf{C}}^{-1})/N$, where

$$\hat{\mathbf{M}}=N^{-1}\sum(\hat{\mathbf{x}}_{ct}^{*'}\hat{\eta}_{ct}-\hat{\mathbf{G}}\hat{\mathbf{r}}_{ct})(\hat{\mathbf{x}}_{ct}^{*'}\hat{\eta}_{ct}-\hat{\mathbf{G}}\hat{\mathbf{r}}_{ct})',$$

$$\hat{\mathbf{G}}=N^{-1}\sum(\hat{\boldsymbol{\beta}}\otimes\hat{\mathbf{x}}_{ct}^{*})'\nabla_\delta\mathcal{F}(\mathbf{z}_{ct},\hat{\boldsymbol{\delta}}),$$

$$\hat{\mathbf{r}}_{ct}=\mathbf{r}_{ct}(\hat{\boldsymbol{\delta}}),$$

and

$$\hat{\eta}_{ct}=\tilde{k}-\hat{\mathbf{x}}_{ct}^{*}\hat{\boldsymbol{\beta}}.$$

A.3 Identification of the Percent Difference in Removals under the Counterfactual of no Change in the Enforcement Guidelines

Here we show that under Secure Communities, the percent difference in the number of removals between the model predictions based on our estimates and the counterfactual prediction in the absence of a change in the enforcement guidelines is point identified for every county-period.

The number of removals can be expressed as the number of fingerprint matches (arrests of unlawfully present immigrants) times the unconditional removal probability $\mathbb{P}$(Removal). In turn, $\mathbb{P}$(Removal) can be expressed as

$$\begin{aligned}\mathbb{P}(\text{Removal}) &= \mathbb{P}(\text{Detainer})\mathbb{P}(\text{ICE Custody}|\text{Detainer})\mathbb{P}(\text{Removal}|\text{ICE Custody, Detainer}) \\ &\quad + (1-\mathbb{P}(\text{Detainer}))\mathbb{P}(\text{ICE Custody}|\text{No Detainer})\mathbb{P}(\text{Removal}|\text{ICE Custody, No Detainer}) \\ &= (q^\ell g \pi^{H\ell} + q^h \pi^{Hh}) f + (1-\mathbb{P}(\text{Detainer})) v^d \frac{1-f}{1-\mathbb{P}(\text{Detainer})}(q^\ell k \pi^{H\ell} + q^h \pi^{Hh}) \\ &= \pi^{H\ell}\left\{\left(q^\ell g + q^h \frac{\pi^{Hh}}{\pi^{H\ell}}\right) f + v^d(1-f)\left(q^\ell k + q^h \frac{\pi^{Hh}}{\pi^{H\ell}}\right)\right\}\end{aligned}$$

While $\pi^{H\ell}$ is not identified, the expression inside curly brackets depends only on identified quantities. Define $A(\epsilon, \xi)$ as the expression inside curly brackets. The percent difference in the number of removals in a given county period between the model predicted and the counterfactual scenario is given by:

$$\begin{aligned}\%\text{ difference} &= \frac{\text{Removals counterfactual} - \text{Removals predicted}}{\text{Removals predicted}} \\ &= \frac{\pi^{H\ell} A(\hat\epsilon^{\text{count}}, \hat\xi^{\text{count}}) - \pi^{H\ell} A(\hat\epsilon^{\text{pred}}, \hat\xi^{\text{pred}})}{\pi^{H\ell} A(\hat\epsilon^{\text{pred}}, \hat\xi^{\text{pred}})} \\ &= \frac{A(\hat\epsilon^{\text{count}}, \hat\xi^{\text{count}})}{A(\hat\epsilon^{\text{pred}}, \hat\xi^{\text{pred}})} - 1\end{aligned}$$

which depends only on identified quantities.

We can similarly recover the counterfactual aggregate percentage change in removals for all counties in our sample by letting predicted removals be equal to removals observed in the data. We also assume that the number of arrests M (fingerprint matches) is the same in the counterfactual. Then the percentage change in removals is

$$\frac{\sum_i \hat M_i A(\hat\epsilon_i^{\text{count}}, \hat\xi_i^{\text{count}})\pi_i^{Hl}}{\sum_i \hat M_i A(\hat\epsilon_i^{\text{pred}}, \hat\xi_i^{\text{pred}})\pi_i^{Hl}} - 1$$

where i is a county-period. Now, assuming the model-predicted deportation rate is equal to the observed deportation rate, $\hat\delta$, we obtain $\pi_i^{Hl} = \hat\delta / A(\hat\epsilon^{\text{pred}}, \hat\xi^{\text{pred}})$, which lets us express the change in removals as a function of observable quantities:

$$\frac{\sum_i \hat M_i \frac{A(\hat\epsilon_i^{\text{count}}, \hat\xi_i^{\text{count}})}{A(\hat\epsilon_i^{\text{pred}}, \hat\xi_i^{\text{pred}})}\hat\delta_i}{\sum_i \hat M_i \hat\delta_i} - 1$$

We can then recover the type-s (e.g. assaults) percentage change in removals as

$$\frac{\sum_i \hat\alpha_{is} \hat M_i \frac{A(\hat\epsilon_i^{\text{count}}, \hat\xi_i^{\text{count}})}{A(\hat\epsilon_i^{\text{pred}}, \hat\xi_i^{\text{pred}})}\hat\delta_i}{\sum_i \hat\alpha_{is} \hat M_i \hat\delta_i} - 1$$

where $\hat\alpha_{is}$ is the share of type-s removals in county period i.

A.4 Counterfactual: Time Evolution of Enforcement Outcomes

In Figure B.6 we present the results of this counterfactual exercise. Each subfigure plots the time evolution of the cross-county distribution of an immigration enforcement outcome along the pipeline. The top panel presents plots for minor offenses cases, while the bottom panel presents plots for serious offenses cases. Panel a illustrates a 5 percentage points across-the-board downward shift of the distribution of $\mathbb{P}$(ICE Custody|Detainer). In the absence of the guidelines, federal efforts ξ^{minor} are predicted to be higher for most counties (see Figure B.5). Strategic substitutability in the local best response of most counties implies reduced collaboration towards minor offenses cases, resulting in lower numbers of ℓ-type arrestees being passed down into ICE custody after a detainer issuance (g, on average, would have fallen considerably).

The direct consequence of lower local collaboration with ICE can be gauged in panel b. The distribution of $\mathbb{P}$(Removal|ICE Custody, Detainer) shifts upwards by around 2 percentage points. This increase in the overall probabilities of removal at the ICE custody stage following a detainer issuance results from a selection effect that interacts with court-level preferences: the weakening of local efforts means that the pool of arrestees that moves onto ICE custody becomes selected towards more h types relative to ℓ types. Because on average $q^h > q^\ell$ (see Table 2), the pool of unlawfully present immigrants facing the removal stage is composed of people more likely be removed, making the conditional removal rate go up.[45]

In contrast, the opposite pattern takes places along the direct track. Panel c illustrates that the distribution of $\mathbb{P}$(Removal|ICE Custody, No Detainer) shifts down by 4 percentage points. This happens because along the direct track, higher federal efforts, ξ^{minor}, and lower local efforts, ϵ^{minor}, both *increase* k (see Table 2), generating a selection effect over the pool of individuals in ICE custody without a detainer shifting its composition towards relatively more ℓ-types. Because $q^h > q^\ell$, this pool is less removable from the point of view of the courts.

Under our counterfactual, outcomes for serious offenses cases behave differently. Panel d of Figure B.6 shows that the counterfactual distribution of $\mathbb{P}$(ICE Custody|Detainer), exhibits something close to a mean-preserving spread, of around a fifth of a standard deviation of the predicted distribution. The increased variance under the counterfactual results from mean reversion of our counterfactual federal enforcement efforts: as panel b in Figure B.5 illustrates, county-periods with low predicted federal enforcement have higher than average counterfactual federal enforcement, and vice-versa. As a result, the local enforcement response is heterogeneous across counties: county-periods with relatively low predicted federal enforcement see their counterfactual local enforcement fall, while county-periods with relatively high predicted federal enforcement see their counterfactual local enforcement increase. On aggregate, these effects do not shift the counterfactual distribution of $\mathbb{P}$(ICE Custody|Detainer), but they do increase its variance. The magnitude of this spread, however, is not as large because, as we reported in Table 3, the average best response slope for serious offenses cases is considerably smaller than for minor offenses cases, leading to a more nuanced response from the local level.

In panel e we then observe an upward shift of around 4 percentage points in the counterfactual distribution of $\mathbb{P}$(Removal|ICE Custody, Detainer) along the detainer track. This aggregate shift results from how removal rates respond to changes in federal enforcement efforts, and not from a systematic selection effect as was the case for minor offenses cases. In particular, from Table 2, notice that for serious offenses, q^ℓ is an increasing function, whereas q^h is a decreasing function of $\xi^{serious}$. Thus, for counties that would have experienced increased federal efforts, on average the resulting increase in ℓ-type removals more than offsets the decrease in h-type removals. Analogously, for counties that would have experienced decreased federal efforts, on average the resulting increase in h-type removals more than offsets the decrease in ℓ-type removals. The absence of guidelines would have magnified the local-federal conflict over immigration enforcement in the following sense: places where the local level reacts by weakening enforcement end up seeing the removal of relatively more ℓ types, precisely the types of unlawfully present immigrants that the county would prefer not be removed.

Finally looking at panel f, we observe a small downward shift along the direct track of the counterfactual distribution of $\mathbb{P}$(Removal|ICE Custody, No Detainer), particularly in the last semesters under consideration. Besides q^ℓ and q^h, k also changes with both federal and local efforts. For serious offenses cases, the strategic substitutability response of most counties reinforces the effect that federal efforts have on the rate at which arrested individuals move onto ICE custody (we estimate k to be increasing in ξ and decreasing in ϵ). As a result, in counties where q^ℓ falls in response to weakened federal enforcement, k also falls leading to relatively less ℓ types removed, and a lower aggregate removal rate. The exercise illustrates that even holding constant the underlying arrestee-pool distribution, the screening forces induced by the immigration enforcement pipeline interact with court-stage preferences in such way that had the guidelines not changed in 2011, the patterns of immigration enforcement resulting from the equilibrium responses of the local level would have antagonized the average large and urban county even more than we observed.

[45] Of course, this exercise supposes court-level preferences remain unchanged under no change in guidelines.

B Online Appendix B: Additional Figures and Tables

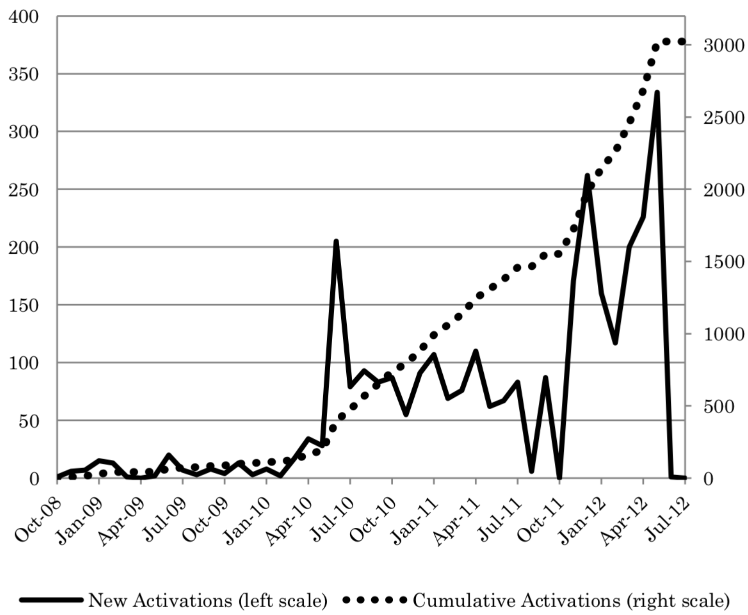


Figure B.1: County Rollout of Secure Communities Activation. The figure shows the yearly (solid line) and cumulative (dashed line) number of counties activated for Secure Communities (source: Cox and Miles (2013)).

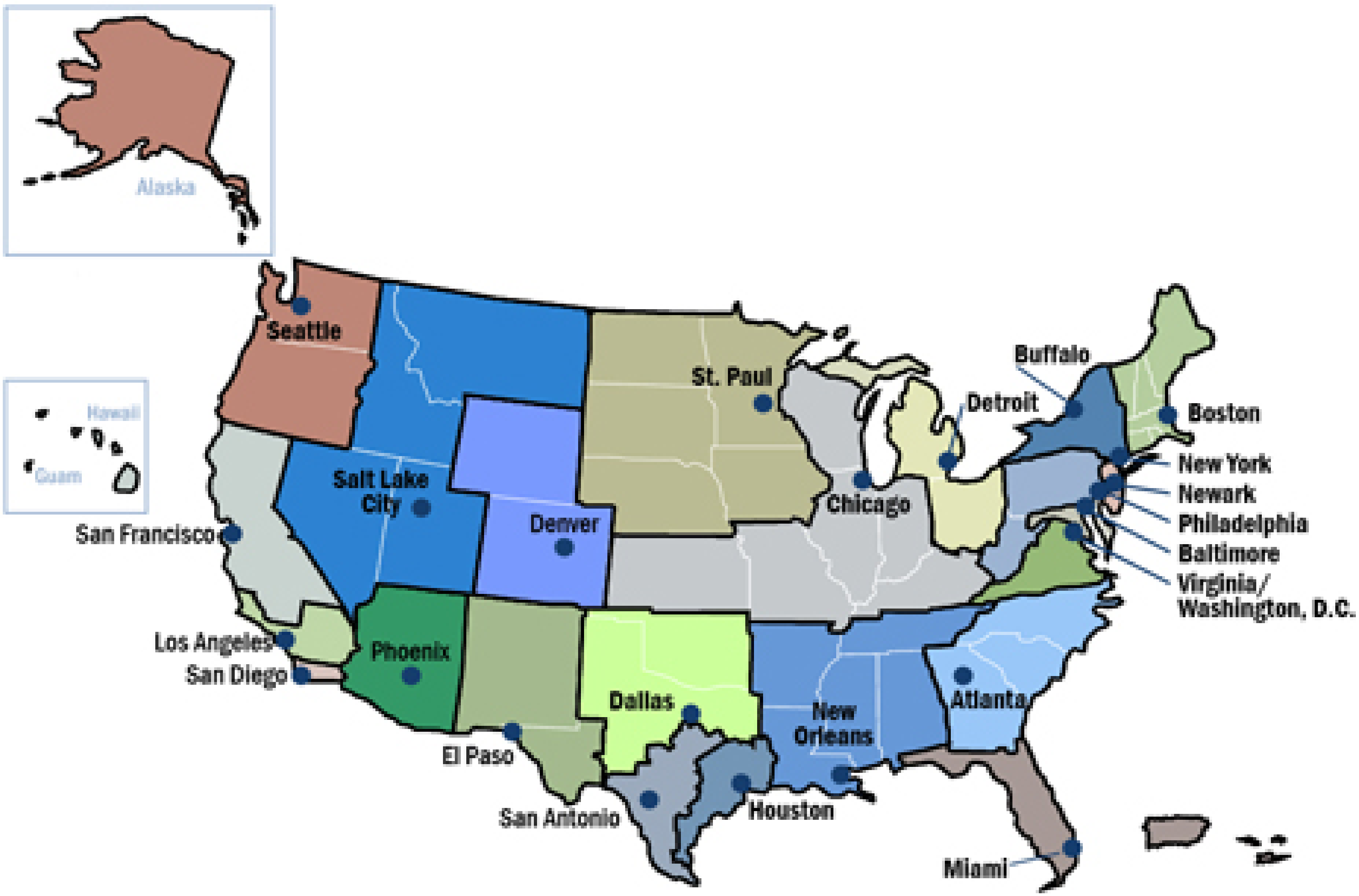


Figure B.2: Immigration and Customs Enforcement Federal Immigration Districts. The figure shows the geographic boundaries of the 24 ICE federal immigration districts and their corresponding headquarters. Source: ICE.

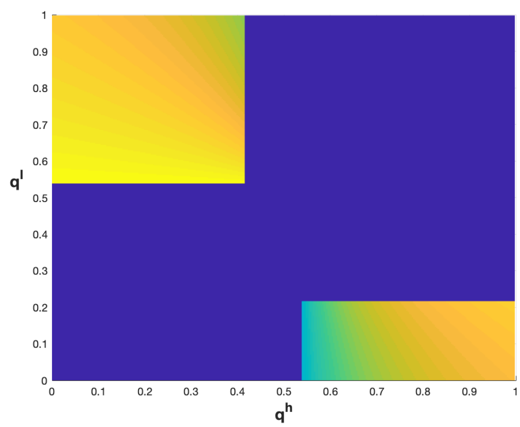


Figure B.3: Example identified set for (q^h, q^ℓ). The figure shows the identified set for (q^h, q^ℓ) from a sample observation.The top left rectangle is $\mathcal{R}_1$. The bottom right rectangle is $\mathcal{R}_2$. The color shade represents the value of the implied g, with higher values of g represented by warmer colors and lower values of g represented by cooler colors. Dark blue represents the region outside the identified set.

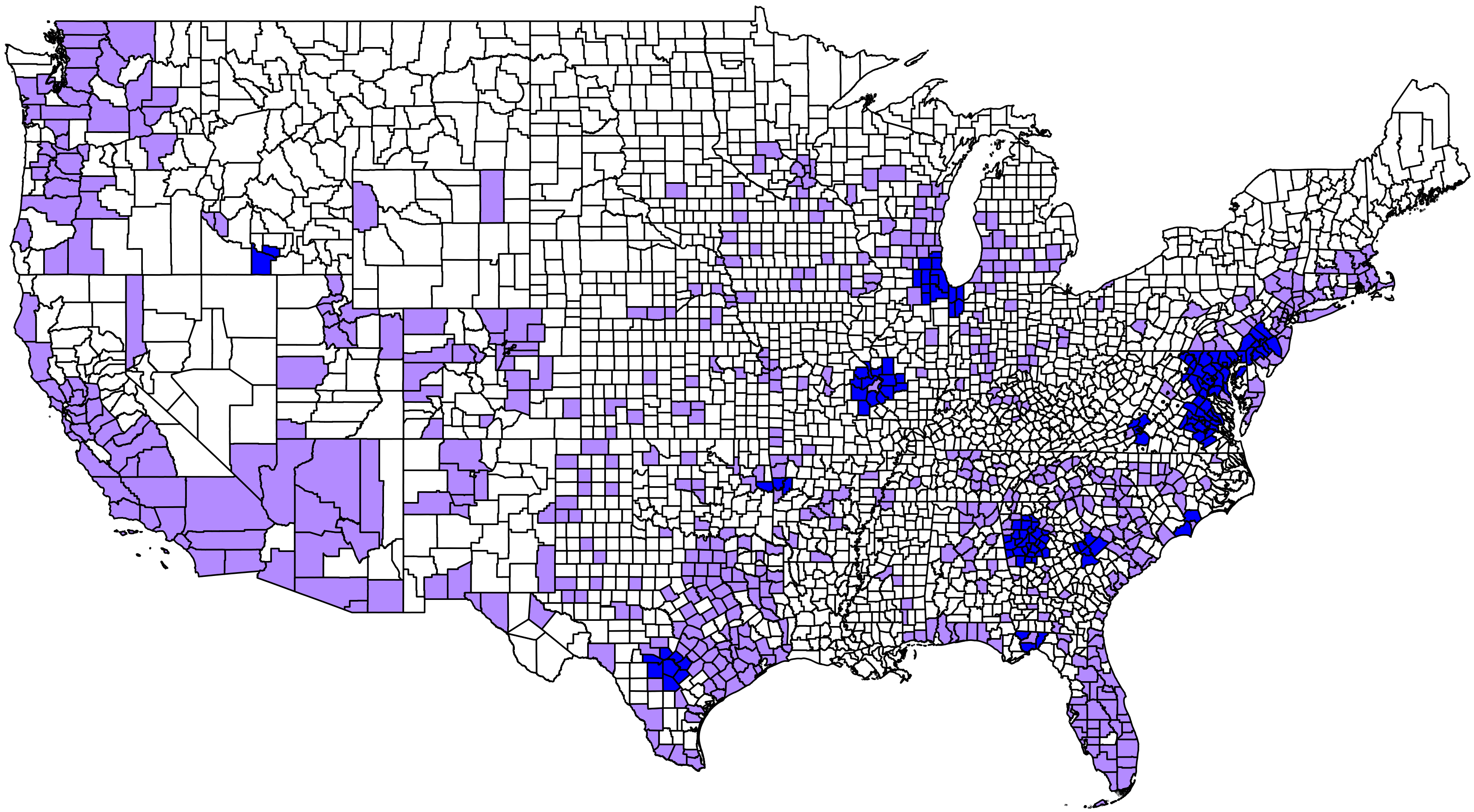
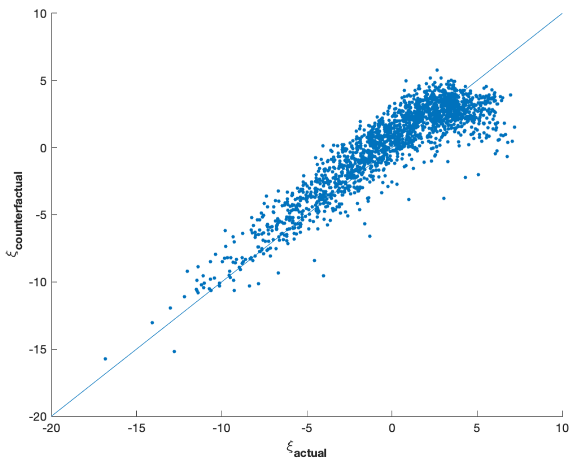
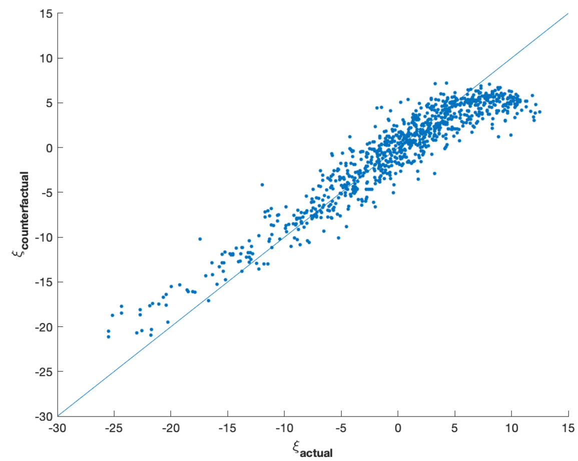


Figure B.4: Counties in the Model Estimation Sample. The map highlights the counties (in lavender) and the cbsa's (in blue) included in the sample used to estimate the model of the immigration enforcement process.

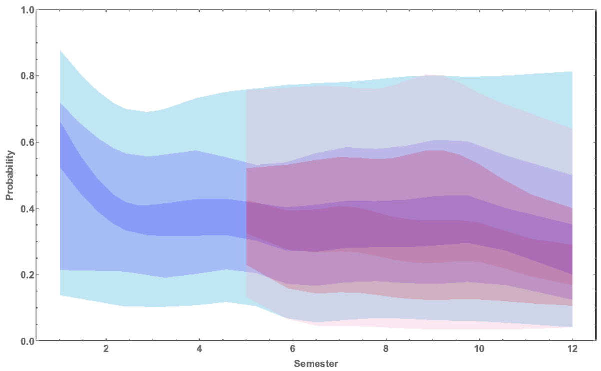


(a) Minor offenses

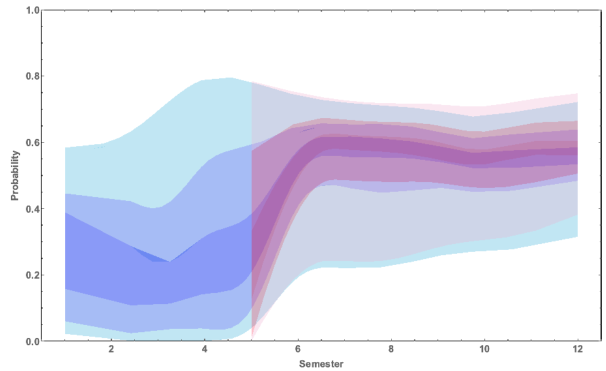


(b) Serious offenses

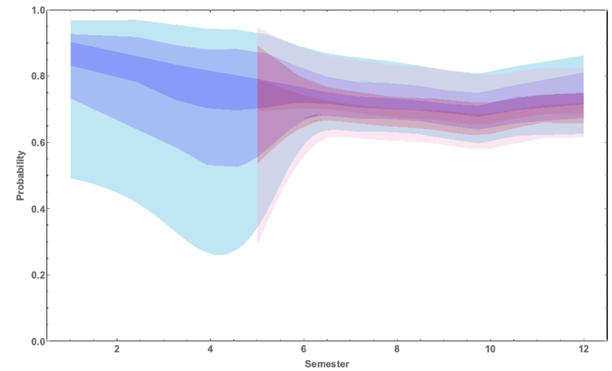
Figure B.5: Scatterplot of Actual vs Counterfactual Federal Efforts. Panel (a) shows a scatterplot of predicted (x-axis) and counterfactual (y-axis) federal immigration enforcement efforts ξ^m for arrestees charged with minor (levels 2-4) offenses. Panel (b) shows a scatterplot of predicted (x-axis) and counterfactual (y-axis) federal immigration enforcement efforts ξ^s for arrestees charged with serious (level 1) offenses. The counterfactual exercise simulates no federal policy guidelines change after 2011-II.



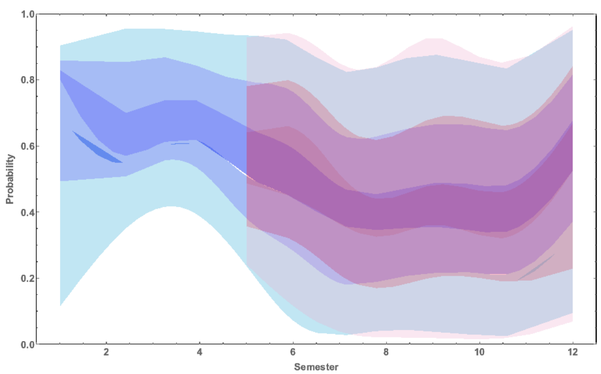
(a) $\mathbb{P}$(ICE Custody|Detainer)



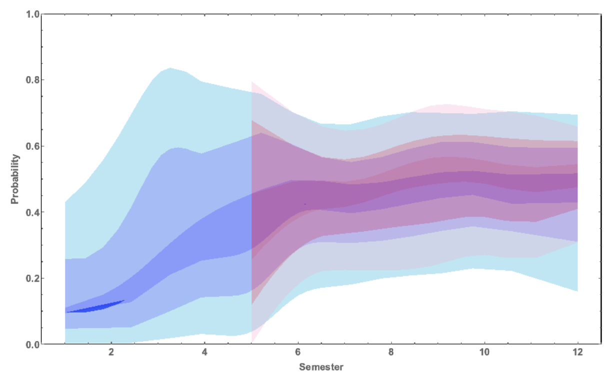
(b) $\mathbb{P}$(Removal|ICE Custody, Detainer)



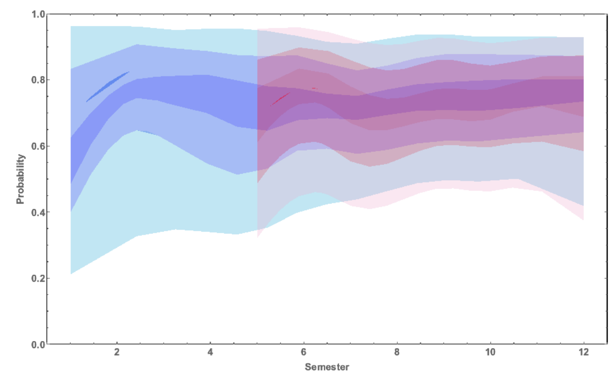
(c) $\mathbb{P}$(Removal|ICE Custody, No Detainer)



(d) $\mathbb{P}$(ICE Custody|Detainer)

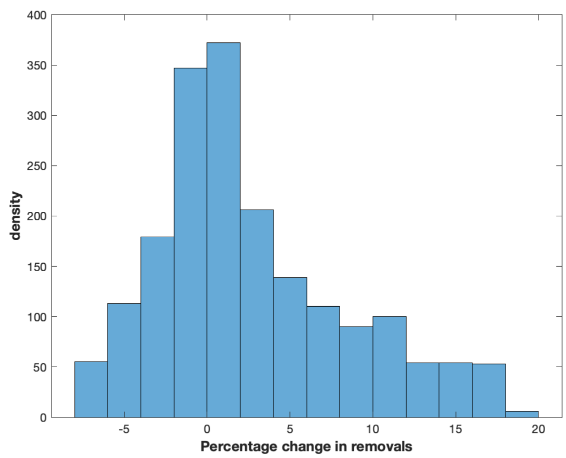


(e) $\mathbb{P}$(Removal|ICE Custody, Detainer)

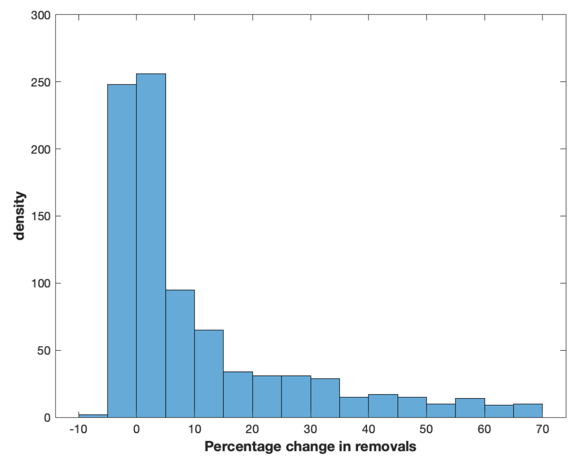


(f) $\mathbb{P}$(Removal|ICE Custody, No Detainer)

Figure B.6: Counterfactual Evolution of Immigration Enforcement Outcomes in the Absence of Guideline Changes. The figure plots the evolution over time of the distribution of immigration enforcement outcomes across counties. The distributions of outcomes predicted by the model are depicted in shades of blue. The distributions of counterfactual outcomes in the absence of guideline changes are depicted in shades of red. The lightest shade regions represent the 10th to 26th and 74th to 90th quantiles. The intermediate shade regions represent the 26th to 42nd and 58th to 74th quantiles. The darkest shade region represents the 42nd to 58th quantiles. The top three panels depict the distributions for minor offenses cases. The bottom three panels depict the distributions for serious offenses cases.

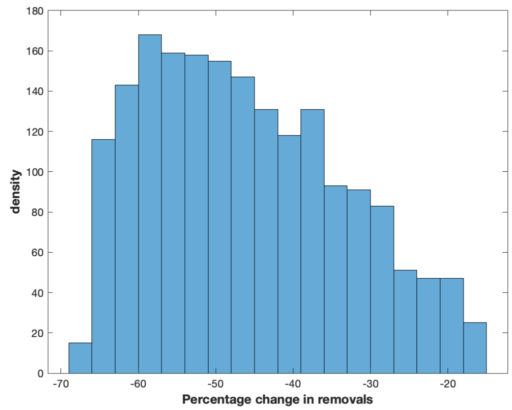


(a) Minor offenses

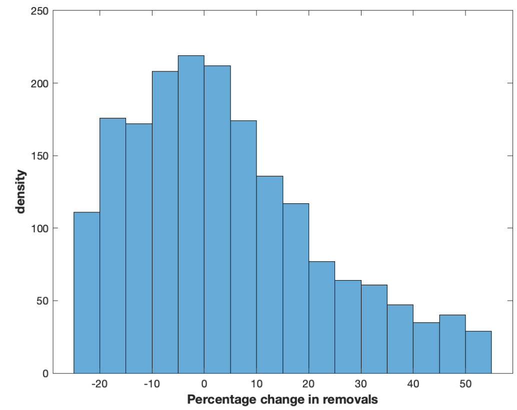


(b) Serious offenses

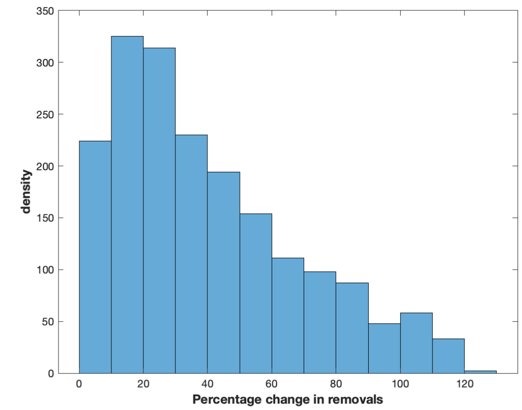
Figure B.7: Distribution of Percent Changes in Removals: Courts Secession Counterfactual vs. Baseline Prediction. Panel (a) shows a histogram of the distribution across county-time periods of percent changes in removals for minor (levels 2-4) offenses, between the courts secession counterfactual and the baseline prediction based on the model estimates. Panel (b) shows a histogram of the distribution across county-time periods of percent changes in removals for serious (level 1) offenses, between the courts secession counterfactual and the baseline prediction based on the model estimates.



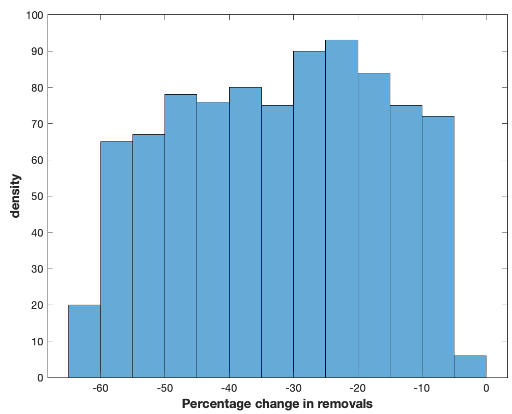
(a) Minor offenses: 10th percentile



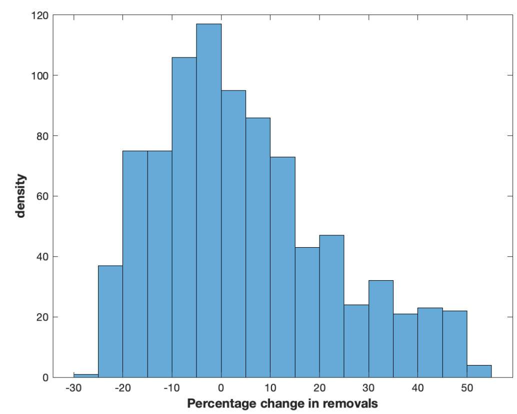
(b) Minor offenses: 50th percentile



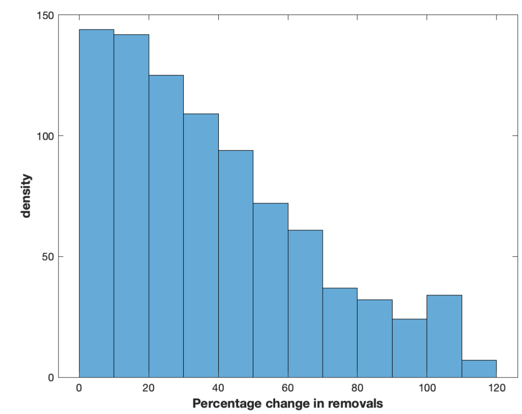
(c) Minor offenses: 90th percentile



(d) Serious offenses: 10th percentile



(e) Serious offenses: 50th percentile



(f) Serious offenses: 90th percentile

Figure B.8: Distribution of Percent Changes in Removals: Courts Severity Counterfactuals vs. Baseline Prediction. The first row shows histograms of the distribution across county-time periods of percent changes in removals for minor (levels 2-4) offenses, between the courts severity homogenization counterfactuals at the 10th,50th and 90th quantile and the baseline prediction based on the model estimates. The second row shows histograms of the distribution across county-time periods of percent changes in removals for serious (level 1) offenses, between the courts severity homogenization counterfactuals at the 10th,50th and 90th quantile and the baseline prediction based on the model estimates.

Minor offenses					
Panel A:	Pre-Policy Change (2009-I – 2011-I)				
	Mean	Std. dev.	Min.	Median	Max.
Arrests	265.8	1105.0	0	18	17268
Detainers	61.2	236.8	0	4	4250
Custodies with detainer	19.8	78.9	0	1	1175
Removals with detainers	10.9	62.3	0	0	1027
Custodies without detainer	37.6	166.7	0	2	3037
Removals without detainer	31.8	155.8	0	0	2632
Observations			1966		
Panel B:	Post-Policy Change (2011-II – 2014-II)				
	Mean	Std. dev.	Min.	Median	Max.
Arrests	113.0	578.6	0	14	17786
Detainers	24.7	128.0	0	2	4131
Custodies with detainer	8.21	56.5	0	0	2430
Removals with detainers	4.06	34.6	0	0	1490
Custodies without detainer	14.1	62.9	0	2	2666
Removals without detainer	10.6	49.8	0	1	1852
Observations			10040		

Serious offenses					
Panel C:	Pre-Policy Change (2009-I – 2011-I)				
	Mean	Std. dev.	Min.	Median	Max.
Arrests	51.8	249.9	0	3	3746
Detainers	13.5	69.0	0	0	1376
Custodies with detainer	6.99	32.0	0	0	493
Removals with detainers	3.32	22.8	0	0	403
Custodies without detainer	14.6	84.4	0	0	1573
Removals without detainer	11.9	77.7	0	0	1507
Observations			2002		
Panel D:	Post-Policy Change (2011-II – 2014-II)				
	Mean	Std. dev.	Min.	Median	Max.
Arrests	52.0	303.7	0	4	9148
Detainers	8.51	57.6	0	0	1999
Custodies with detainer	3.54	29.5	0	0	1289
Removals with detainers	1.66	16.9	0	0	734
Custodies without detainer	7.02	37.4	0	1	1271
Removals without detainer	5.60	33.6	0	0	1189
Observations			10202		

Table B.1: Descriptive Statistics for Immigration Enforcement Variables. The table presents summary statistics for the variables related to the immigration enforcement process under Secure Communities. We report counts of events aggregated at the county-semester level of observation. All variables in panels A and B refer to minor offenses (level 2-4 under ICE's classification). All variables in panels C and D refer to serious offenses (level 1 under ICE's classification). Panels A and C report summary statistics from 2009-I to 2011-I (before the June 2011 policy guidelines change). Panels B and D report summary statistics from 2011-II to 2014-II (after the June 2011 policy guidelines change). Arrests are measured as the number of fingerprint matches under Secure Communities. Our source for arrests, detainers, and ICE custodies is a FOIA to DHS. Our source for removals and for classifying ICE custodies between those with and without detainers is TRAC.

Panel A:	All counties above median undocumented share				
	Mean	Std. dev.	Min.	Median	Max.
Log population	10.9	1.43	6.66	10.7	16.1
Undocumented share	0.017	0.018	0.0028	0.011	0.14
Hispanic share	0.12	0.15	0.00023	0.063	0.96
Bachelor degree share	0.21	0.100	0.037	0.18	0.71
Democratic party share	0.41	0.15	0.081	0.40	0.92
Rural	0.52	0.50	0	1	1
Services share	0.59	0.084	0.28	0.59	0.90
Log distance ICE office	4.87	1.85	-9.97	5.18	6.71
287(g) Program	0.029	0.17	0	0	1
Observations			1547		
Panel B:	Counties in the model estimation sample				
	Mean	Std. dev.	Min.	Median	Max.
Log population	11.8	1.25	8.13	11.8	16.1
Undocumented share	0.022	0.020	0.0028	0.016	0.14
Hispanic share	0.16	0.17	0.015	0.093	0.96
Bachelor degree share	0.24	0.10	0.075	0.22	0.70
Democratic party share	0.43	0.15	0.081	0.42	0.89
Rural	0.28	0.45	0	0	1
Services share	0.62	0.079	0.36	0.62	0.88
Log distance ICE office	4.57	2.46	-9.97	5.06	6.65
287(g) Program	0.069	0.25	0	0	1
Observations			566		

Table B.2: Descriptive Statistics for the County Sample. The table presents summary statistics of the county characteristics of our sample of counties. Panel A reports summary statistics for all counties with undocumented population above median. Panel B reports summary statistics for all counties above median undocumented population that satisfy the conditions required for estimation of the immigration enforcement process model. Log Population is taken from the 2010 Census. Undocumented share is an estimate of the number of unlawfully present individuals in 2010 (its construction is described in Appendix C). Democratic party share is an average of the 2008 and 2012 Democratic Presidential vote shares, taken from David Leip's Electoral Atlas. Bachelor degree share is measured as the fraction of the adult population with at least a bachelor's degree. Hispanic share is measured as the fraction of the population who is hispanic. Services share is measured as the fraction of the employed population working in the services sector. Bachelor degree share, Hispanic share, and Services share are taken from the 2006-2010 waves of the American Communities Survey. Rural is a dummy variable indicating whether the county is considered non-metropolitan according to the National Center for Health Statistics at the Center for Disease Control. Distance to ICE office is measured as the log of the number of miles between the county centroid and the county centroid of the corresponding ICE district office seat, and computed directly by us. 287(g) Program is a dummy variable indicating whether the county or any city in the county was ever part of the 287(g) program, taken from Steil and Vasi (2014).

Panel A:	Minor Offenses				
	ξ	ϵ	ζ_l	ζ_h	$\pi^{Hh}/\pi^{H\ell}$
ξ	1.00				
ϵ	-0.49	1.00			
ζ^l	0.00	0.08	1.00		
ζ^h	0.00	-0.05	-0.10	1.00	
$\pi^{Hh}/\pi^{H\ell}$	0.34	-0.37	-0.15	0.13	1.00
Panel B:	**Serious Offenses**				
ξ	1.00				
ϵ	-0.39	1.00			
ζ^l	0.00	-0.04	1.00		
ζ^h	0.00	-0.12	0.02	1.00	
$\pi^{Hh}/\pi^{H\ell}$	0.32	-0.44	-0.04	0.16	1.00

Table B.3: Correlation Matrix of Enforcement Efforts and Preference Alignment. The table shows the correlation matrix of selected enforcement variables. Panel A shows the correlation coefficients for minor offenses while panel B shows the coefficients for serious offenses.

Minor offenses						
Panel A:	Pre-Policy Change (2009-I – 2011-I)					
	Mean	Std. dev.	Min.	Median	Max.	Obs.
x1 = $\mathbb{P}$(detainer)	0.26	0.17	0	0.24	1	1110
x2 = $\mathbb{P}$(ICE custody, detainer)	0.11	0.12	0	0.076	1	1025
x3 = $\mathbb{P}$(removal, detainer)	0.064	0.10	0	0.020	1	936
y1 = $\mathbb{P}$(ICE custody | no detainer)	0.22	0.22	0	0.15	1	1098
y2 = $\mathbb{P}$(removal | no detainer)	0.17	0.21	0	0.10	1	979
Panel B:	Post-Policy Change (2011-II – 2014-II)					
	Mean	Std. dev.	Min.	Median	Max.	Obs.
x1 = $\mathbb{P}$(detainer)	0.23	0.17	0	0.19	1	4474
x2 = $\mathbb{P}$(ICE custody, detainer)	0.085	0.11	0	0.054	1	4324
x3 = $\mathbb{P}$(removal, detainer)	0.054	0.075	0	0.029	1	3866
y1 = $\mathbb{P}$(ICE custody | no detainer)	0.23	0.22	0	0.16	1	4449
y2 = $\mathbb{P}$(removal | no detainer)	0.18	0.20	0	0.11	1	4312

Serious offenses						
Panel C:	Pre-Policy Change (2009-I – 2011-I)					
	Mean	Std. dev.	Min.	Median	Max.	Obs.
x1 = $\mathbb{P}$(detainer)	0.29	0.25	0	0.23	1	750
x2 = $\mathbb{P}$(ICE custody, detainer)	0.20	0.20	0	0.14	1	634
x3 = $\mathbb{P}$(removal, detainer)	0.083	0.13	0	0.034	1	584
y1 = $\mathbb{P}$(ICE custody | no detainer)	0.40	0.33	0	0.32	1	716
y2 = $\mathbb{P}$(removal | no detainer)	0.33	0.32	0	0.23	1	621
Panel D:	Post-Policy Change (2011-II – 2014-II)					
	Mean	Std. dev.	Min.	Median	Max.	Obs.
x1 = $\mathbb{P}$(detainer)	0.19	0.16	0	0.15	1	2559
x2 = $\mathbb{P}$(ICE custody, detainer)	0.092	0.11	0	0.062	1	2392
x3 = $\mathbb{P}$(removal, detainer)	0.051	0.071	0	0.028	0.67	2143
y1 = $\mathbb{P}$(ICE custody | no detainer)	0.24	0.21	0	0.18	1	2539
y2 = $\mathbb{P}$(removal | no detainer)	0.19	0.20	0	0.13	1	2454

Table B.4: Immigration Enforcement Pipeline: Conditional Probabilities. The table presents summary statistics for the conditional probabilities related to the immigration enforcement pipeline under Secure Communities, for the sample of observations used for estimation. We report conditional probabilities at the county-semester level of observation. All variables in panel A and B refer to minor offenses (level 2-4 under ICE's classification). All variables in panel C and D refer to serious offenses (level 1 under ICE's classification). Panels A and C report summary statistics from 2009-I to 2011-I (before the June 2011 policy guidelines change). Panels B and D report summary statistics from 2011-II to 2014-II (after the June 2011 policy guidelines change).

	f (1)	g (2)	k (3)	q^l (4)	q^h (5)
Log population	0.44	-0.09	-0.59	-0.09	0.17
	(0.11)	(0.20)	(2.12)	(0.65)	(0.62)
Undocumented share	9.08	-7.57	-28.73	-9.70	5.95
	(6.94)	(11.24)	(14.30)	(15.17)	(13.28)
Hispanic share	2.74	-0.09	0.33	1.38	0.35
	(1.10)	(1.48)	(3.26)	(2.51)	(2.24)
Bachelor degree share	0.78	1.67	1.58	0.07	-0.96
	(1.19)	(2.50)	(3.41)	(3.16)	(3.07)
Rural	-0.38	-0.13	0.48	0.01	0.16
	(0.28)	(0.70)	(2.20)	(1.05)	(0.94)
Services share	-0.53	-1.53	-1.18	1.72	0.64
	(2.03)	(3.82)	(5.06)	(5.00)	(4.46)
Democratic party share	-1.28	-1.30	0.42	-2.22	-0.19
	(0.85)	(1.49)	(2.83)	(2.09)	(1.90)
Log distance ICE office	0.14	-0.10	-0.11	0.005	0.006
	(0.02)	(0.04)	(2.11)	(0.586)	(0.586)
287(g) program	0.59	1.74	-1.49	-0.82	1.09
	(0.33)	(0.56)	(2.22)	(0.94)	(0.98)
Observations			2348		

Table B.5: Coefficients on the covariates of the logistic regressions for the enforcement probabilities. Minor Offenses. The table reports the β coefficients for the logistic regressions in equations (17)-(20) for minor offenses. Log Population is taken from the 2010 Census. Undocumented share is an estimate of the number of unlawfully present individuals in 2010 (its construction is described in Appendix C). Democratic party share is an average of the 2008 and 2012 Democratic Presidential vote shares, taken from David Leip's Electoral Atlas. Bachelor degree share is measured as the fraction of the adult population with at least a bachelor's degree. Hispanic share is measured as the fraction of the population who is hispanic. Services share is measured as the fraction of the employed population working in the services sector. Bachelor degree share, Hispanic share, and Services share are taken from the 2006-2010 waves of the American Communities Survey. Rural is a dummy variable indicating whether the county is considered non-metropolitan according to the National Center for Health Statistics at the Center for Disease Control. Distance to ICE office is measured as the log of the number of miles between the county centroid and the county centroid of the corresponding ICE district office seat, and computed directly by us. 287(g) Program is a dummy variable indicating whether the county or any city in the county was ever part of the 287(g) program, taken from Steil and Vasi (2014). Coefficients for time dummies are omitted. Standard errors are robust to arbitrary heteroskedasticity.

	f (1)	g (2)	k (3)	q^l (4)	q^h (5)
Log population	1.08	-0.09	-1.08	-0.10	0.19
	(0.28)	(0.33)	(7.30)	(1.04)	(1.00)
Undocumented share	18.33	35.48	-63.46	-14.21	31.17
	(17.19)	(17.48)	(50.32)	(20.97)	(20.78)
Hispanic share	-0.06	-0.61	3.86	0.005	0.68
	(2.32)	(2.31)	(10.19)	(2.594)	(2.31)
Bachelor degree share	0.24	2.70	0.50	-0.57	0.59
	(3.13)	(4.39)	(10.79)	(4.40)	(3.23)
Rural	-0.10	-0.77	-1.96	-1.20	-0.14
	(1.21)	(1.79)	(7.75)	(2.03)	(1.84)
Services share	-2.21	-8.03	3.43	2.29	-3.48
	(5.43)	(6.47)	(17.03)	(7.01)	(5.20)
Democratic party share	-7.72	-6.71	8.75	-0.66	-1.45
	(2.12)	(2.61)	(9.20)	(2.98)	(2.28)
Log distance ICE office	0.09	0.003	-0.10	0.005	0.02
	(0.04)	(0.075)	(7.27)	(0.972)	(0.97)
287(g) program	-2.91	-0.09	1.98	-0.30	1.00
	(0.67)	(0.79)	(7.47)	(1.29)	(1.28)
Observations			1101		

Table B.6: Coefficients on the covariates of the logistic regressions for the enforcement probabilities. Serious Offenses. The table reports the β coefficients for the logistic regressions in equations (17)-(20) for serious offenses. Log Population is taken from the 2010 Census. Undocumented share is an estimate of the number of unlawfully present individuals in 2010 (its construction is described in Appendix C). Democratic party share is an average of the 2008 and 2012 Democratic Presidential vote shares, taken from David Leip's Electoral Atlas. Bachelor degree share is measured as the fraction of the adult population with at least a bachelor's degree. Hispanic share is measured as the fraction of the population who is hispanic. Services share is measured as the fraction of the employed population working in the services sector. Bachelor degree share, Hispanic share, and Services share are taken from the 2006-2010 waves of the American Communities Survey. Rural is a dummy variable indicating whether the county is considered non-metropolitan according to the National Center for Health Statistics at the Center for Disease Control. Distance to ICE office is measured as the log of the number of miles between the county centroid and the county centroid of the corresponding ICE district office seat, and computed directly by us. 287(g) Program is a dummy variable indicating whether the county or any city in the county was ever part of the 287(g) program, taken from Steil and Vasi (2014). Coefficients for time dummies are omitted. Standard errors are robust to arbitrary heteroskedasticity.

Panel A:	Minor offenses							
	By offense type				By demographics			
	(1) No conv.	(2) Drug	(3) Traffic	(4) Other	(5) Mex.	(6) C. Am.	(7) L.P.R.	(8) Prior Rem.
Courts secede	0.2	0.8	1.3	0.7	0.5	1.0	0.1	0.5
Courts severity homogenized								
10th percentile	-38.8	-40.0	-40.5	-38.8	-39.6	-38.2	-38.5	-39.8
50th percentile	1.1	0.2	1.6	2.2	0.1	4.0	5.0	0.5
90th percentile	27.6	27.4	30.0	29.6	26.4	32.7	33.4	27.5
Panel B:	Serious offenses							
	By offense type				By demographics			
	(1) Burglary	(2) Smuggling	(3) Assault	(4) Other	(5) Mex.	(6) C. Am.	(7) L.P.R.	(8) Prior Rem.
Courts secede	5.3	5.0	2.1	5.5	4.3	6.1	6.6	4.6
Courts severity homogenized								
10th percentile	-25.8	-24.1	-18.5	-23.0	-24.1	-25.2	-25.5	-24.5
50th percentile	3.0	3.0	1.8	3.5	1.7	6.0	6.2	2.2
90th percentile	29.5	28.6	23.3	29.1	25.8	35.6	35.6	27.2

Table B.7: Counterfactuals: courts seceding and severity by type of removal. The table reports the overall percentage changes in removals across all county-periods between different counterfactual scenarios and the baseline prediction based on the model estimates for different categories of removals following the description in appendix A.3. The categories of offenses (no conviction, drug possession, traffic violations, and other for minor, and burglary, assaults, smuggling –which includes drug trafficking and smuggling aliens–, and other for serious) are changes in removals issued against unlawfully present immigrants in the county-semester committing those offenses. L.P.R. refers to changes in removals for legal permanent residents. Mexican and Central American shares are the fractions of removals issued against immigrants of those nationalities in the county-semester. Prior removal refers changes in removals for individuals who had been deported before.

C Online Appendix C: Construction of Variables

C.1 Undocumented Share

We use different sources to construct estimates of the undocumented population at the county level. Warren and Warren (2012), Passel (2005) and the Department of Homeland Security provide estimates of the undocumented population at the state level for different years and use a residual method that combine the number of people entered in the US and the number of non citizens from Census and other survey data. Estimates at substate level are almost nonexistent. One exception is Hill and Johnson (2011), who use information from tax returns to estimate the undocumented population at the county and at the zip-code levels in California. Since 1996, unauthorized immigrants, who lack social security numbers, have been allowed to file federal tax returns using a unique identifier, the Individual Taxpayer Identification Number, or ITIN. Hill and Johnson (2011) show that this measure is highly correlated with the estimates of undocumented population at the state level. This is not surprising; although many undocumented immigrants lack a social security number, they still have an incentive to file taxes in order to collect tax refunds. Our preferred measure of the undocumented population combines the number of Hispanic non citizens from the ACS, the state level estimates from Warren and Warren (2012), and the number of ITIN filers.

$$\text{undocumented}_{county} = \text{undocumented}_{state2010} * \frac{1}{2}\left(\frac{\text{hisp noncitizens}_{county}}{\text{hisp noncitizens}_{state2010}} + \frac{ITIN_{county}}{ITIN_{state2010}}\right)$$

C.2 Consistency between Model and Data

C.2.1 Assigning ICE Arrests to Detainer or Direct Track

Secure Communities data on ICE arrests (custodies) do not have information on whether a detainer was issued or not. To identify custodies from detainers, we use detainers data from TRAC on the universe of detainers, which include detainers on SC as well as other detainers. TRAC detainers data include information on whether the individual ended up in ICE custody and we can apply the custody-detainer ratio to the SC detainers to recover the number of custodies from SC detainers under the assumption that SC detainers and overall detainers have a similar composition. To avoid inconsistencies in the arrests and removals data between both sources (TRAC and Secure Communities), we define p as the constant such that $C = Dp + (M - D)p = Mp$, where C is ICE custodies, D is detainers and M is local arrests. p is the probability that an immigrant is taken into ICE custody if the probability is the same along the detainer and the direct tracks. It follows that

$$C = D\underbrace{\left(p + \epsilon\frac{M-D}{M}\right)}_{p_1} + (M-D)\underbrace{\left(p - \epsilon\frac{D}{M}\right)}_{p_2}$$

. Now, ϵ allows the probabilities to differ across tracks, while keeping them consistent with the observed C. The idea is to make ϵ increasing in the custody-detainer ratio from TRAC: $s \equiv \frac{C|D_{trac}}{D_{trac}}$. Using the restrictions that $p_1, p_2 \in [0, 1]$ we can recover a lower bound $\underline{\epsilon}$ and an upper bound $\overline{\epsilon}$. Additionally, we can impose the restrictions $R|D \leq C|D$ and $R|noD \leq C|noD$ to construct the two bounds for ϵ. Then, we can set $\epsilon = (1-s)\underline{\epsilon} + s\overline{\epsilon}$ where the lower bound is $\underline{\epsilon} = \max\{-C/(M-D), -(M-C)/D, -(C - R|D * M/D)/(M-D)\}$ and the upper bound is $\overline{\epsilon} = min\{C/D, (M-C)/(M-D), C/D - M * R|noD/(D*(M-D))\}$.

C.2.2 Consolidating Counties into CBSA

Our empirical strategy puts significant demands on the data. In particular, we need positive counts at each step of the deportation process. The number of counties that satisfy these requirements is limited (650 in the sample for minor offenses). In an effort to work with a larger sample, we group neighboring counties not in the initial sample that fall into core-based statistical areas (CBSA), a census definition that includes both metropolitan statistical areas and micropolitan areas. We are able to add 19 CBSA that satisfy the requirements for our estimation strategy, assigning them covariate values computed as weighted averages of the covariates across counties within each of these CBSA's. Figure B.4, illustrates in dark blue the CBSA's in our sample.