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

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**Abstract**

Selection forces often confound the effects of policy changes. In the immigration enforcement context, we tackle this challenge tracking arrested immigrants along the deportation pipeline, isolating local and federal efforts. 80% of counties

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exhibit strategic substitutabilities in responding to federal enforcement, while the federal level is very effective at directing its efforts toward cooperative counties. We estimate that changes in the profile of immigration cases, and not weakened federal efforts, drove the reduction in deportations following a 2011 shift in federal priorities. Reducing immigration-court discretion and removing their dependence from the executive would have a significant impact on deportations.

**Keywords:** Immigration enforcement, federalism, law enforcement, crime.

**JEL Codes:** D73, D78, H73, H77, J15, J61, K37

# 1 Introduction

Quantifying the effects of policies, especially of those not uniformly implemented across regions, poses serious challenges: the bureaucracies mediating their enforcement have preferences and face constraints that shape their willingness and ability to effect policy. In federalist environments, policy outcomes can further depend on multiple layers of agents with conflicting preferences.[1] Selection effects, –changes in the behavior or the composition of those over which the policy is intended to apply– can affect the implementation of policies as well. Immigration enforcement in the US is a case in point. First, the number and characteristics of deported immigrants can vary with features of the labor market or of law enforcement because interior immigration cases begin when an unlawfully present immigrant has contact with the

[1]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).

police. Second, local decisions affect many margins of immigration policy because it is difficult for the federal level to implement policy without local-level aid. For example, sheriffs can refuse to hand over arrested immigrants to the federal immigration agency. Demographics, partisanship, and proximity to borders all shape local preferences over immigration policy. As a result, there is ample variation in the extent of *alignment* of preferences over enforcement between jurisdictional levels. Third, deportation patterns vary with the supply of criminal offenses, the arresting behavior of law enforcement, or cross-county migration, all of which are endogenous to changes in immigration enforcement.

In this paper we develop a framework that leverages the institutional details of the Secure Communities program –the main channel of interior immigration enforcement between 2008 and 2014–, to decompose the variation in immigration enforcement outcomes (e.g., deportation rates by type of offense or by demographic characteristics) between what can be attributed to local enforcement efforts, to federal enforcement efforts, and to changes in the composition of the pool of unlawfully present immigrants going through what we will refer to as the immigration enforcement pipeline. This decomposition allows us to establish that 80 percent of counties exhibit strategic substitutabilities in their response to changes in federal enforcement, and that more Democratic and less Hispanic counties were more eager to undo the federal efforts by weakening their collaboration with Immigration and Customs Enforcement (ICE), the agency in charge of federal immigration enforcement. We also uncover a remarkable effectiveness by ICE at directing its efforts toward counties where it can expect more local collaboration. These features of the strategic environment are key to understand three substantive questions we to tackle in this study.

First, how selection drives the apparent effects of policy changes: in mid 2011 the Obama administration undertook a major shift in federal immigration enforcement policy, retreating from the prosecution of immigrants accused of misdemeanors and minor crimes, and refocusing on those accused of serious crimes. As Figure 1 (panel a) illustrates, trends in federal requests for local collaboration (detainers) and deportations of minor offenses cases show a sharp reversal following the policy change. In apparent contrast with the spirit of the policy, however, the trend reversal is present also for cases involving serious offenses (panel b). We find that the pattern for serious offenses cases was not driven by defiance to the new policy. Enforcement efforts did strengthen in line with the new guidelines, and were partially undone by the local level response. Rather, a large selection effect over the immigrant pool entering the pipeline took place based on two changes: more disagreement between the federal and the local levels on how amenable to deportation these cases were, and a shift in the profile of immigration cases prioritized by ICE that made some previously attractive targets for removal no longer so. We estimate that changes in enforcement efforts alone were considerable, and would have led to 2.3 *additional* serious offense deportations for every deportation happening right before the policy change. The selection effects were even larger and of opposite sign, however, more than undoing the increased federal efforts towards serious offenses, and explaining the average 28 percent fall in serious offenses deportations following the change in guidelines. Absent any change in the composition of the pool of immigrants entering the pipeline, 78 percent of counties would have observed more deportations of serious offense cases following the change in federal guidelines. In contrast, enforcement efforts towards minor offenses weakened marginally and would have led to 3.4 percent less deportations. Thus, most of the 53 percent fall in minor offense deportations can be attributed to selection effects, illustrating the importance of distinguishing between the enforcement and selection margins of policy change when evaluating the effects of policy reform.

Second, how preference misalignment across jurisdictions shapes policy outcomes: our framework allows us to assess the impact of the 2011 ICE guidelines on preferences over removals. We explicitly avoid modeling the enforcement effort choices of the local and federal levels. While this limits our ability to undertake standard welfare evaluation, we can map implied preferences onto observable case characteristics. This is a convenient albeit indirect way to trace some welfare implications of the policy change: regardless of stances over immigration policy, the local and federal levels were both more sympathetic towards the removal of immigrants accused of more serious offenses. Under the new policy, the pool of cases shifted towards assault and drug trafficking cases, and towards cases of Mexican nationals the average county was less willing to remove. It also shifted towards cases of un-convicted immigrants the average county was more willing to remove. These results highlight that conflict over policy across vertical jurisdictions is a first-order driver of policy outcome heterogeneity. They also suggest that the implementation of very effective enforcement technologies 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, how features of the institutional design steer the effects of policy changes: we undertake two counterfactual exercises gauging the importance of the immigration courts in shaping deportation outcomes. 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 courts would increase the number of removals, particularly for serious offenses and in the period after the new guidelines were implemented. Second, we evaluate the discretionary component of removal decisions by the immigration courts simulating a scenario where their severity is homogenized. Forcing all counties to be as lenient as the county at the 10th percentile of severity, aggregate removals would be 38 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 court decisions could have a significant impact on removals.

Distinguishing local and federal enforcement choices from selection (unobserved characteristics of the pool of arrested unlawfully present individuals) and from each other is challenging 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 can depend on arrest-pool characteristics. A purely descriptive analysis of the movement of arrestees along the pipeline would not allow such a decomposition. For example, an increase in the number of arrestees handed to ICE by the local level could be the result of a change in the local level's preferences over collaboration, or of a compositional change in the pool of arrestees towards those more amenable to deportation from the local level's perspective, without any change in its preferences.

Using data on the universe of cases going through the immigration enforcement pipeline between 2009-2014, our empirical analysis exploits the following institutional features: First, a key technological innovation introduced under Secure Communities: the FBI automatically sends to ICE the fingerprints of every person arrested by local police, allowing the agency to locate potential targets for deportation without the acquiescence of local law enforcement. As a result, the pool of arrestees entering the pipeline is *not* selected based on local-level preferences. Second, the full discretion of ICE agents to issue detainer requests asking local law enforcement for collaboration holding the arrestees. As a result, local enforcement choices have no (direct) effect on the likelihood of a detainer request, allowing us to isolate federal enforcement efforts from this first step. Third, the full discretion of the local level to comply with a detainer request (by holding or releasing the arrestee before ICE agents show up). As a result, federal enforcement choices have no (direct) effect on this compliance decision, allowing us to isolate local enforcement efforts from this second step. Lastly, once the arrestee is in ICE custody a deportation court proceeding may begin. The comparison of observed transition rates across the five key steps of the pipeline (arrest to detainer, detainer to custody, custody to removal, arrest to custody without detainer, custody without detainer to removal), which all depend on the composition of the pool of arrestees and of the enforcement efforts, allows us to disentangle selection from the enforcement choices.

Leveraging these institutional features we avoid imposing assumptions about the underlying game played between federal and local levels, such as specific utility functions, beliefs, or information sets. We consider this to be an advantage of our approach. A similar one could be applied to settings with sequentially structured institutions. 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 sequential choices inducing selection into subsequent stages. Explicitly modeling the institutional details of these pipelines can similarly allow distinguishing patterns of selection from the choices of the players.

Strategic interactions between levels of government arise in many settings besides ours, such as school funding, tax enforcement, the foster care system, or environmental protection and regulation (see Cascio et al. (2013); Mann (2011); Rechtschaffen and Markell (2003)). A central challenge in 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 environment shaping policy choices and outcomes. Perhaps except for Agarwal et al. (2014); Bohn et al. (2015); Fredriksson and Mamun (2008); Knight (2002), there is scant empirical literature highlighting how strategic responses across levels of government shape heterogeneity in policy outcomes. In our context, the local response to the federal level is a source of heterogeneity in enforcement intensity and in the effects of the policy. We address these concerns by leveraging the details of an institutional setting featuring both federalism and policy overlap across levels of government.

The literature on federalism emphasizes that the extent of decentralization should be driven by preference heterogeneity and the salience of local information (Hooghe and Marks (2003); Inman and Rubinfeld (1997); Lockwood (2002); Oates (1999); Tullock (1969)). It 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)). In contrast, here we point to the local-federal alignment in preferences as a key consideration for understanding variation in policy choice and policy outcomes, and recover the local enforcement response to changes in federal enforcement. We show that differences in preferences over immigrants with different criminal offense records are a key driver of the conflict between both levels. The results from our counterfactual exercises also highlight the importance of both court independence and court discretion in decentralized environments.

We also contribute to the literature on the political economy of immigration policy and law enforcement.[2] Scholars have found a strong correlation between the size of the Hispanic community and the passage of ordinances weakening immigration enforcement (Boushey and

[2]A related literature studies "chilling effects" of increased immigration enforcement, for example in school attendance (Dee and Murphy (2018)), geographic mobility (Amuedo-Dorantes et al. (2013)), or social welfare program take-up (Alsan and Yang (2018); Watson (2014)).

Luedtke (2011); Steil and Vasi (2014)), and between the ethnicity of local law enforcement and 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 (Magazinnik (2018); 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.

## 2 Immigration policy under Secure Communities

The 21st century has seen increased variation across space in immigration policy as local, state, and federal levels have all attempted to exert increasing influence over immigration enforcement. The most prominent federal effort in this period is the Secure Communities program, our main focus of attention. The program oversaw the largest expansion of interior immigration enforcement in U.S. history (Kalhan (2013)). Participation in Secure Communities was mandatory.[3] Its rollout began in 2008, but the program was officially discontinued in November 2014 after a re-directioning of the program in 2011 was unable to quell the significant controversy and local and state resistance it generated. Despite its demise, Secure Communities constituted a radical innovation, on both the institutional and the technological

[3]ICE designed Secure Communities in response to a Congressional directive to "identify every criminal alien, at the prison, jail, or correctional institution in which they are held." (*Consolidated Appropriations Act of 2008*). We provide additional details in Appendix A.5.

fronts. We now describe how the program operated.

**First step: the federal level.** Secure Communities restricted the ability of local police to exercise discretion over immigration enforcement. Under standard procedure following a local 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 ICE, for comparison against its Automated Biometric Identification System (IDENT). If there is a match to an 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.[4] 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 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.[5] This is in sharp contrast to

[4]ICE is organized geographically into 24 federal enforcement districts (see Figure B.1).

[5]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)).

the ample local discretion possible under CAP or 287(g).[6] [7]

Once ICE officials identify a person of interest 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 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 about the arrestee. This includes the severity of the offenses charged, 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 to pick up the person of interest. ICE officers follow a series of priority guidelines. They may also 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.

[6]Officers could alternatively not collect the fingerprints of an arrestee they believe may be illegally present, but this would constitute malpractice and would not allow the police to establish his criminal status (Gulasekaram and Ramakrishnan (2015)). The arresting behavior of the police, however, may have changed in response to the introduction of Secure Communities, a first order source of selection we will deal with below.

[7]Section 287(g) of the Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) of 1996 allows for cooperation agreements whereby local law enforcement officials receive training and authority to enforce federal immigration law. As of 2021, 85 such agreements are in place (see: www.ice.gov/287g).

We leverage a 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.[8] Increased federal enforcement led to pressure from local governments and immigration advocacy groups, which, together with the forthcoming presidential election, were key factors driving the policy change. The new guidelines, outlined in a series of memos, refocused federal efforts and resources away from the prosecution of immigrants accused of minor offenses or immigration violations, and towards those accused of serious crimes. It also specified a long list of prioritization criteria:

> "ICE must prioritize the use of its enforcement personnel, detention space, and removal assets to ensure... the agency's enforcement priorities... 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... to decide to what degree to enforce the law against a particular individual" (Morton (2011)).

In practice, the Secure Communities program used a four-level classification for offenses. Level 1 being the most serious includes homicide, kidnappings, sexual assault, and terrorist activity. Levels 2 and 3 include less serious crimes such as burglary, theft, traffic offenses, small drug offenses, and immigration violations (for the full list, 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.

**Second step: the local level.** Local law enforcement can exercise discretion as well, but in the next stage of the process. Once ICE has submitted a detainer request, local law

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

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, 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.[9] 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 local and federal levels is made manifest: because ICE moves first when deciding whether to issue a detainer, arrestees for whom a detainer is issued are necessarily highly desired by the federal level, irrespective of ICE officers' beliefs about the local level's reaction. This need not be the case for arrestees over whom ICE abstains from issuing a detainer; this set will include all arrestees ICE is uninterested in, and other arrestees who are of interest but over 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, local officials may not honor the detainer. As a result, the rate of compliance with detainer requests will be informative about the extent of alignment of preferences between both levels.

Variation in local cooperation is partly driven by local preferences over the presence of

[9] Several appeals and state Supreme Court rulings have affirmed the right of local agencies to exercise discretion 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)). Moreover, some counties have argued that holding an arrestee who has not otherwise been charged with a crime, in response to a detainer, may constitute a due process violation (Pham (2006)).

unlawfully present immigrants. It also depends on the costs of compliance. First, holding arrestees for longer is expensive, and diverts resources from law enforcement.[10] 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 lobbying local governments and crafting legislation to limit local collaboration. 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.

**Third step: ICE custody and removal.** ICE can bring arrestees into its custody in two ways: picking them up pursuant to a detainer request, –the 'detainer track'–, or picking them up following an unannounced visit to the local jail, –the 'direct track'–. For arrestees with an issued detainer, the local level's compliance decision fully determines the likelihood they move into ICE custody. In contrast, for those without an issued detainer, both federal and local efforts shape the likelihood they move into ICE custody.[11] This distinction and

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[10] In its non-cooperation ordinance, for example, the Cook county 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... enforcement of ICE detainers places a great strain on our communities by eroding the public trust the sheriff depends on to secure the accurate reporting of criminal activity..." (Cook county board of commissioners, Sept. 7, 2011)

[11] 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.

availability of data from both tracks will be crucial for the identification strategy we lay down below. In either case, immigrants in ICE custody go on to an immigration court deportation proceeding. Under US law, immigration courts are *not* part of the judicial branch; they constitute a division within the Department of Justice, and thus, are part of the federal executive branch. As such, the outcomes at the removal stage may 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. Immigrants under ICE custody are free to waive their right to an immigration proceeding, in which case they are directly removed.

## 3 Data description

**The immigration enforcement pipeline.** Our data comes from Freedom of Information Act 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 2008 and 2015. These data include: the number of fingerprint submissions from local jails with matches to the IDENT database, of detainers issued by ICE, of individuals in ICE custody, of removals, and the ICE priority level based on crime seriousness. We consider level 1 as serious crimes and levels 2 and above as minor crimes, based on TRAC's classification which relies on ICE's official priority levels and has been consistent over time. We use the number of fingerprint matches as our measure of local arrests of unlawfully present individuals. We also collected data from the *Transactional Records Access Clearinghouse* (TRAC) at Syracuse University. TRAC has up to date record-level datasets of detainers and Secure Communities removals with information from 2002 to the present. It includes 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.[12] We aggregate 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.

**County sample and characteristics.** Figure B.2 illustrates the rollout of the Secure Communities program across counties. Throughout we restrict attention to counties with an estimated share of unlawfully present immigrants above median (0.3 percent of the population), where federal-local conflict over immigration can be relevant. Elsewhere immigration enforcement is not a locally salient issue, and we observe no variation in immigration outcomes. We collected an array of additional county-level characteristics related to local preferences over immigration enforcement, and report summary statistics for them in Table B.3.

**Patterns of immigration enforcement outcomes.** In Appendix A.6 we look at patterns of immigration enforcement outcomes before and after the 2011 guidelines estimating county fixed effects models where we recover the average probability of moving to a subsequent

[12]The definition of a period involves a bias-precision trade-off: defining longer periods allows us to have county-period cells with more cases in them, thus allowing more precise estimation of the underlying conditional probabilities. Our model assumes, however, the underlying parameters are constant within a period, so longer periods make this assumption less likely to hold. We believe that aggregating the enforcement cases at the semester level balanced this trade-off evenly. For additional details of our procedure, see Appendix C.

step of the pipeline before and after the policy change. We find that removals per arrest are indistinguishable between pre and post-guidelines 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 moving along the immigration enforcement pipeline. These results motivate our subsequent empirical strategy and modeling approach.

# 4 A model of the immigration enforcement pipeline

We present a framework to disentangle the three key sources of variation in the patterns of immigration enforcement described above: local enforcement, federal enforcement, and selection in the composition of the pool of arrestees. We capture the misalignment of preferences over removals between the federal and local levels by allowing for time-varying unobserved heterogeneity in the composition of this pool, and leverage the institutional details of the pipeline to trace how the pool of arrestees is filtered along the process. This information allows us to separately recover federal and local immigration enforcement efforts, while also allowing us to abstain from taking stances over utility functions, beliefs, or other details of the implicit game between both levels. We only rely on two substantial and readily interpretable assumptions made explicit below.

## 4.1 The immigration enforcement process

Arrested immigrants vary in observed and unobserved (to us) characteristics. Conditional on the observables, most prominently the seriousness of the offense motivating the arrest, the local and federal levels may disagree about the case's degree of removal priority. The top of Figure 2 describes the distribution of the relevant unobserved heterogeneity in the pool of arrestees *in a given county and time period.* $\pi^{L\ell}$ is the fraction of arrestees who are low priority for ICE ($L$) and for the county ($\ell$), while $\pi^{Hh}$ is the fraction of arrestees who are high priority for both ICE ($H$) and the county ($h$). The higher these fractions, the more aligned their preferences. In contrast, $\pi^{Lh}$ is the fraction of arrestees ICE is not interested in removing ($L$), but the local level would prefer to remove ($h$). $\pi^{H\ell}$ is the fraction of arrestees ICE would like to remove ($H$), but the local level would not ($\ell$). The higher these fractions, the more misaligned their preferences. We now illustrate how the pipeline's structure allows us to relate observed conditional probabilities to the pool's composition and enforcement choices. The process begins when, following a fingerprint match, the FBI informs the ICE district office about the arrest of an unlawfully present immigrant.

**The detainer track.** We illustrate the first path on the left side of Figure 2, where the ICE district office decides to issue a detainer request. Detainers are not issued for $L$ types: $\mathbb{P}(\text{Detainer}|L) = 0$[13]. We define $f \equiv \mathbb{P}(\text{Detainer}|H)$ as the probability of a detainer issuance for $H$ arrestees. It depends on the intensity of federal immigration enforcement efforts. Conditional on observed characteristics, this probability is constant within time periods (semesters in our empirical application). 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 offense. Moreover, from the point of view of ICE, all $H$ types are on average equally desirable irrespective of their local type, $h$ or $\ell$. $\{h, \ell\}$ are residual characteristics of the arrestee directly relevant to the local level only. Part may represent characteristics observed by the local level

[13] This is not an assumption; it simply corresponds to the definition of an $L$ type.

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 detainer issuance stage. For example, forward-looking ICE agents might to want make inter-temporal promises of lenient future behavior to obtain the sheriff's collaboration over a person they believe the local level may not want to remove. When a new fingerprint match arrives, it is unlikely that ICE agents will be able to keep such a promise. This is particularly so because each ICE district is simultaneously responsible for more than a hundred different counties. Under Assumption 1, our first observable at the county×time period level is

$$\mathbb{P}(\text{Detainer}|\text{Arrest}) = (\pi^{H\ell} + \pi^{Hh})f \equiv P_{D|A}. \tag{1}$$

$P_{D|A}$ depends on federal enforcement $f$, and on the composition of the pool of arrestees. All $L$ types are filtered out at this stage. Moreover, because the federal level does not select detainers based on local preferences, the composition of the resulting pool of arrestees with detainers directly reflects the relative fractions of $\ell$ and $h$ types among $H$ types.

County-level officials must then decide whether to honor the detainer. They will hand in $Hh$ type arrestees: $\mathbb{P}(\text{ICE Custody}|\text{Detainer}, Hh) = 1$. In contrast, there is conflict over $\ell$ types. The county's willingness to enforce immigration can thus be captured by the conditional probability of honoring such detainers: $\mathbb{P}(\text{ICE Custody}|\text{Detainer}, H\ell) \equiv g$. Thus, the probability that arrestees with detainers move into ICE custody is

$$\mathbb{P}(\text{ICE Custody}|\text{Detainer}) = 1 \times \frac{\pi^{Hh}}{\pi^{H\ell} + \pi^{Hh}} + g \times \frac{\pi^{H\ell}}{\pi^{H\ell} + \pi^{Hh}} \equiv P_{C|D}, \tag{2}$$

which we observe at the county×time period level. Across periods, $P_{C|D}$ can vary because among $H$ types the pool is shifting between $h$ and $\ell$ types (selection), or because local immigration enforcement is changing (through $g$), or both. The discretion of the local level in honoring detainers provides an exclusion restriction: $P_{C|D}$ does not vary with federal immigration enforcement $f$.

Once in ICE custody, removal decisions depend on immigration courts, whose preferences may not fully align with those of ICE. To be fully general we must allow court-stage removal rates to depend on the remaining source of unobserved heterogeneity, $j \in \{\ell, h\}$: we denote by $q^j \equiv \mathbb{P}(\text{Removal}|\text{ICE Custody}, \text{Detainer}, j)$ the conditional probability of removal of an $Hj$ type. These depend on the intensity of federal enforcement, and on the preferences of the district courts. They do not, however, depend on local enforcement, an additional exclusion restriction implied by the pipeline. The last observable along the detainer track is

$$\mathbb{P}(\text{Removal}|\text{ICE Custody}, \text{Detainer}) = q^\ell \frac{g\pi^{H\ell}}{g\pi^{H\ell} + \pi^{Hh}} + q^h \frac{\pi^{Hh}}{g\pi^{H\ell} + \pi^{Hh}} \equiv P_{R|C,D}. \tag{3}$$

It varies with court and federal immigration enforcement (through $(q^\ell, q^h)$), with local immigration enforcement (through $g$), and with the distribution of types. Equation (3) reveals a key pattern of selection induced by the structure of the pipeline: if the courts' preferences are strongly aligned with the county's preferences ($q^h > q^\ell$), a fall in local immigration enforcement, $g$, will *increase* $P_{R|C,D}$. The reason is a screening effect from local immigration enforcement: when the county reduces enforcement, the share of $H\ell$ individuals who reach ICE custody falls. The pool of custodies becomes selected towards $Hh$ individuals, which courts are more willing to remove.

**The direct track.** Resource and political economy constraints limit ICE's ability to issues detainers. The right-hand side path in Figure 2 illustrates the alternative path. ICE agents can attempt taking an immigrant into custody by visiting the jail of detention. This 'direct track' can be useful over $H$ types for whom it might be convenient to avoid issuing a detainer.

Similar to the detainer track, only $H$ types are at play as ICE has no interest over $L$ types. ICE has limited resources. After deciding whom to issue detainer requests for, it will not undertake a prison visit for every remaining $H$-type fingerprint match. 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 jails targeting immigrants who did not receive a detainer request. Conditional on a visit, the local level collaborates over any $Hh$ types requested. Thus, $\mathbb{P}(\text{ICE Custody}|\text{No Detainer}, Hh) = v^d$. 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, which must depend on a combination of federal and local efforts. Thus, $\mathbb{P}(\text{ICE Custody}|\text{No Detainer}, H\ell) = v^d k$, and we observe

$$\mathbb{P}(\text{ICE Custody}|\text{No Detainer}) = v^d \frac{(1-f)\pi^{Hh}}{1-(\pi^{Hh}+\pi^{H\ell})f} + v^d k \frac{(1-f)\pi^{H\ell}}{1-(\pi^{Hh}+\pi^{H\ell})f} \equiv P_{C|ND}, \quad (4)$$

so that $P_{C|ND}$ varies with federal enforcement efforts –through $v^d$, $k$, and $f$–, with local enforcement efforts –through $k$–, and with the composition of types of arrestees.

Once immigrants reach ICE custody, the court system makes deportation decisions. Our second and last key assumption is that conditional on offense severity and type $\{h, \ell\}$, the track through which arrestees 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 $j \in \{h, \ell\}$,*

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

We believe assumption 2 is very weak, as it only restricts the removal probabilities across tracks *within* a given county and time period. 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 over the immigrant. 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 would 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 reaching ICE custody as

$$\mathbb{P}(\text{Removal}|\text{ICE Custody, No Detainer}) = q^{\ell}\frac{k\pi^{H\ell}}{k\pi^{H\ell}+\pi^{Hh}} + q^{h}\frac{\pi^{Hh}}{k\pi^{H\ell}+\pi^{Hh}} \equiv P_{R|C,ND}. \quad (5)$$

$P_{R|C,ND}$ varies with court enforcement –through $(q^{\ell}, q^{h})$–, with federal enforcement –through $(q^{\ell}, q^{h})$, and $k$–, with local enforcement –through $k$–, and with changes in the distribution of types. Equations (1)-(5) constitute all the restrictions the pipeline provides, relating observed transition probabilities to enforcement parameters and the immigrant pool composition. The restrictions embedded in equations (1)-(5) allow for the detainer and direct tracks to be dependent, as they jointly depend on $f$, $g$, and $k$. These probabilities, in turn, will jointly vary with federal and local-level immigration enforcement efforts, so our model captures the covariance structure of the observed transition probabilities from both tracks.

# 5 Identification and estimation

Identification of our model relies on two types of variation in the data. First, within a county-period, we use variation in transition rates across stages of the pipeline, and exploit our ability to track changes in the arrest pool composition as immigrants move across its stages. This allows us to fully control for selection, but provides us only with a partial identification result: we show that the observed transition rates i) constrain $(q^\ell, q^h)$ to lie inside a strict subset of $[0,1]^2$, and ii) point identify $(g, k, v^d(1-f)/f)$ given a value for $(q^\ell, q^h)$. This part of the analysis is non-parametric. Second, we use variation across counties and time periods in characteristics capturing preferences and constraints related to immigration, to model $(f, g, k, q^\ell, q^h)$ as parametric functions of those characteristics, and exploit the exclusion restrictions and dependencies across them implied by the institutional details of the pipeline.

## 5.1 Partial identification: using variation along the pipeline

Our ability to track how the underlying composition of the pool of arrested immigrants changes along the stages of the pipeline *within county-time periods* allows us to obtain a set of relationships $\Psi(\boldsymbol{\theta}, \mathbf{w})$ between enforcement probabilities $\boldsymbol{\theta} \equiv (f, g, k, q^\ell, q^h, v^d)$ and observables $\mathbf{w} \equiv (P_{D|A}, P_{C|D}, P_{R|C,D}, P_{C|ND}, P_{R|C,ND})$ that *does not* depend on the pool composition $(\pi^{Hh}, \pi^{H\ell})$. Because the distribution of types is unobserved and can be correlated with the enforcement choices at all the different stages, $\Psi(\boldsymbol{\theta}, \mathbf{w})$'s independence from $(\pi^{Hh}, \pi^{H\ell})$ implies we effectively control for all selection considerations changing the composition of the pool over time, and mediating the relationship between observed transition rates and enforcement probabilities. These considerations include endogenous responses from the supply of offenses changing the types of immigrants entering the pipeline, changes in federal or local priorities, in the arresting behavior of law enforcement in response to immigration enforcement –including charging behavior by prosecutors or bail or parole decisions by judges–, and even in cross-county migration of immigrants in response to enforcement pressure in neighboring counties. Thus, our empirical strategy does not assume the exogeneity of the economic or criminal behavior of immigrants, nor of the prosecutorial behavior of law enforcement.

In Appendix A we formally characterize $\Psi(\boldsymbol{\theta}, \mathbf{w})$, showing it is indeed independent of $(\pi^{Hh}, \pi^{H\ell})$, and that it has only two degrees of freedom, namely the probabilities of removal for $h$ and $\ell$ types conditional on ICE custody, $(q^h, q^\ell)$. For a given vector of observed transition rates $\mathbf{w}$, knowledge of $(q^h, q^\ell)$ pins down the probability with which the county hands in to ICE an $\ell$ type arrestee for whom a detainer was issued, $g$, the probability with which the county hands in to ICE an $\ell$ type arrestee for whom no detainer was issued, $k$, and the product of the district prison-visit probability with the odds ratio of no detainer to detainer issuances for $H$ types, $v^d(1-f)/f$. Here we provide some intuition for this result. First, define $\alpha \equiv \pi^{Hh}/\pi^{H\ell}$. In what follows we will refer to this ratio as the extent of *preference alignment* between the federal and the local levels, as it measures the fraction of arrestees in a given county-period over which local and federal levels agree, per arrestee over which they disagree. Being one-dimensional, it is a convenient summary statistic capturing the extent of conflict between local and federal levels.

Consider (3), and notice that *given* $(q^h, q^\ell)$, $P_{R|C,D}$ can be written as a function of $g$ and $\alpha$ only. Now consider a county where, for example, $q^\ell > q^h$, and compare two scenarios for the initial arrestee pool: a low alignment scenario, with say, one $Hh$ person for every five $H\ell$ people, and a high alignment scenario with say, one $Hh$ person for every two $H\ell$ people. Compared to the high alignment scenario, the low alignment scenario requires that $g$, the probability with which the local level collaborates over $H\ell$ types, be relatively low. Otherwise, too many $H\ell$ arrestees would have moved into ICE custody for the observed removal rate to be the same as in the scenario with high alignment. This is, (3) implies a monotonic *increasing* relationship between $g$ and $\alpha$ given the observed removal rate of arrestees in ICE custody with a detainer. Now consider (2), which can also be written as a function of $g$ and $\alpha$ only, and compare the same two alignment scenarios. Under both, all $Hh$ arrestees move into ICE custody. In the low alignment scenario, however, there are relatively few $Hh$ types. For $P_{C|D}$ to be the same in both scenarios, it must be that a relatively large share of $H\ell$ arrestees move into ICE custody. Thus, $g$ must be high compared to the high alignment case. This is, (2) implies a monotonic *decreasing* relationship between $g$ and $\alpha$ given the observed ICE custody rate of arrestees with detainers. As a result, there is a unique pair $(g, \alpha)$ that satisfies (2) and (3). A similar logic applies to the comparisons across all other stages of the pipeline.

In an analogy to linear panel settings where taking first differences eliminates the time-invariant unobservable, here we eliminate the unobserved heterogeneity by taking quotients of transition rates along and across tracks of the immigration enforcement pipeline, within a time period. Although the pipeline structure allows us to control for selection non-parametrically, it does not provide enough information to separately identify each enforcement probability. The $(q^h, q^\ell)$ are partially identified, however:

**Proposition 1.** *Suppose that* $\mathbf{w} = (P_{D|A}, P_{C|D}, P_{R|C,D}, P_{C|ND}, P_{R|C,ND}) \in (0,1)^5$*, and define* $\underline{m} \equiv min\{P_{R|C,D}, P_{R|C,ND}\}$*,* $\overline{m} \equiv max\{P_{R|C,D}, P_{R|C,ND}\}$*, and* $\tilde{q} = (P_{R|C,ND} - P_{C|D}P_{R|C,D})/(1 - P_{C|D})$*. The observed vector of conditional probabilities* $\mathbf{w}$ *for a given county-period is consistent with any pair* $(q^h, q^\ell) \in \mathcal{R}(\mathbf{w})$*, where* $\mathcal{R}(\mathbf{w}) = \mathcal{R}_1 \cup \mathcal{R}_2$*, and:*

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

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

**Proof.** See Appendix A. □

This result follows from jointly imposing all the constraints relating observed moments to unobserved probabilities, 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 pipeline transitions alone: observed conditional probabilities are consistent with a high removal rate for $\ell$ types and a low removal rate for $h$ types, or vice versa. Finally, observe that if $g$ were point identified, we would recover $\alpha = \pi^{Hh} \,/\, \pi^{H\ell}$ using equation (A.1).

## 5.2 Identification: using variation across counties and time periods

Now we show how exploiting cross-county and cross-semester variation in observable characteristics, and explicitly modeling a set of exclusion restrictions implied by the institutional details of the immigration enforcement pipeline, we can identify the enforcement probabilities $\boldsymbol{\theta}$, and additionally recover measures of immigration enforcement effort by the federal and local levels. We incorporate these restrictions explicitly by relying on a parametric (logistic) assumption on the enforcement probabilities. We can directly work with the log odds forms:

$$\log\left(f_{ct}/(1-f_{ct})\right) \equiv \tilde{f}_{ct} = \mathbf{x}'_{ct}\boldsymbol{\beta}^{f} + \xi_{ct} \tag{6}$$

$$\log\left(g_{ct}/(1-g_{ct})\right) \equiv \tilde{g}_{ct} = \mathbf{x}'_{ct}\boldsymbol{\beta}^{g} + \epsilon_{ct} \tag{7}$$

$$\log\left(k_{ct}/(1-k_{ct})\right) \equiv \tilde{k}_{ct} = \mathbf{x}'_{ct}\boldsymbol{\beta}^{k} + \kappa_{\epsilon}\epsilon_{ct} + \kappa_{\xi}\xi_{ct} + \eta_{ct} \tag{8}$$

$$\log\left(q^{\tau}_{ct}/(1-q^{\tau}_{ct})\right) \equiv \tilde{q}^{\tau}_{ct} = \mathbf{x}'_{ct}\boldsymbol{\beta}^{q\tau} + \gamma^{\tau}\xi_{ct} + \zeta^{\tau}_{ct}, \qquad \tau \in \{\ell, h\} \tag{9}$$

We allow all enforcement probabilities above to vary with observable county characteristics and semester dummies, $\mathbf{x}_{ct}$, so the model can rationalize differences in enforcement rates across county-periods with similar enforcement efforts. In fact, in (6) we allow ICE's probability of detainer issuance towards $H$ arrestees to vary with a measure of federal enforcement effort, $\xi_{ct}$. In (7) we allow the county's probability of compliance with detainers over $H\ell$ arrestees to vary with a measure of local enforcement effort $\epsilon_{ct}$. These equations incorporate two key exclusion restrictions: $f$ does not vary with local enforcement efforts, and $g$ does not vary with federal enforcement efforts. Because the relationships in (6) and (7) have already controlled for selection –as they do not depend on $(\pi^{H\ell}, \pi^{Hh})$–, we can attribute differences in enforcement probabilities between counties with similar $\mathbf{x}_{ct}$'s to differences in efforts, $\xi_{ct}$ and $\epsilon_{ct}$.

In (8) we allow the probability that $H\ell$ arrestees move into ICE custody along the direct track to depend on both local and federal enforcement efforts.[14] The $\eta_{ct}$ represent variation in $k_{ct}$ not captured by our model. In (9) we allow the probability of deportation of $Hj$ arrestees to vary with federal enforcement efforts, capturing the dependence of immigration courts on the executive branch, but also allowing for a discrepancy between their preferences. The $\zeta^{\tau}_{ct}$ represent variation in $q^{j}_{ct}$ not captured by our model. Equation (9) also incorporates an exclusion restriction: although $q^{\ell}$ and $q^{h}$ can be dependent with federal enforcement efforts, they do not vary with local enforcement efforts, as the counties are irrelevant at the removal stage. We also assume that $v^{d}$ does not vary across counties within a federal enforcement district-period.[15] Equations (6)-(9) make explicit the dependence structure across enforcement

[14]This allows us to capture 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) and by the county (for example, it may try to resist handing in an arrestee to ICE).

[15]The logistic choice allows us to recover the relevant coefficients as closed forms from the

probabilities: $g$ covaries with $k$ through the immigration enforcement effort of the local level, $f$ covaries with $k$ through the immigration enforcement effort of the federal level, and $q^\ell$ and $q^h$ covary with $f$ through the immigration enforcement effort of the federal level.

Consider a candidate $(q^\ell_{ct}, q^h_{ct})$ for all $(c, t)$, which we collect in the vectors $(\mathbf{q}^\ell, \mathbf{q}^h)$, such that each pair is feasible given the observed transition probabilities $\mathbf{w}_{ct}$: $(q^\ell_{ct}, q^h_{ct}) \in \mathcal{R}(\mathbf{w}_{ct})$. $\Psi(\boldsymbol{\theta}, \mathbf{w}_{ct})$ then pins down the unique triple $(g_{ct}, f_{ct}, k_{ct})$ consistent with $(q^\ell_{ct}, q^h_{ct})$. With $(g_{ct}, f_{ct})$ in hand, we can estimate the regressions in (6) and (7), and recover the implied federal and local immigration enforcement efforts $\xi_{ct}$ and $\epsilon_{ct}$ as their residuals. The vectors of 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 $(\mathbf{q}^\ell_{ct}, \mathbf{q}^h_{ct})$, $\mathbf{W} = (\mathbf{w}_1, ..., \mathbf{w}_n)$ where $\mathbf{w}_c = (\mathbf{w}'_{c1}, ..., \mathbf{w}'_{ct})'$, and $\mathbf{X} = (\mathbf{x}'_1, ..., \mathbf{x}'_n)'$. Using these efforts as regressors, we can then estimate regressions (8)-(9). Note that the minimized sums of squared residuals of these regressions are closed-form functions of $(\mathbf{q}^\ell_{ct}, \mathbf{q}^h_{ct})$, $\mathbf{W}$, and $\mathbf{X}$ as well:

$$
\begin{aligned}
\mathcal{S}^k(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) &= \sum_c \sum_t (\tilde{k}_{ct} - \mathbf{x}'_{ct}\boldsymbol{\beta}^k_{ols} - \kappa_{\epsilon,ols}\hat{\epsilon}_{ct} - \kappa_{\xi,ols}\hat{\xi}_{ct})^2 \\
\mathcal{S}^\tau(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) &= \sum_c \sum_t (\tilde{q}^\tau_{ct} - \mathbf{x}'_{ct}\boldsymbol{\beta}^{q\tau}_{ols} - \gamma^\tau_{ols}\hat{\xi}_{ct})^2, \quad \tau \in \{\ell, h\}.
\end{aligned} \tag{10}
$$

Our exclusion restrictions imply that at the true $(\mathbf{q}^\ell, \mathbf{q}^h)$ we recover the true values of the left and the right-hand side variables in the three regression equations in (10), and thus their

corresponding log odds linear regressions, but any choice of functional form for the enforcement probabilities would suffice. For computational convenience, we rely on (A.4) to re-write (6) in terms of $\overline{f}_{ct} \equiv v^d_t(1 - f_{ct})/f_{ct}$, instead of working directly with (6), and estimate $\log(\overline{f}_{ct}) = \log(v^d_t) - \mathbf{x}'_{ct}\boldsymbol{\beta}^f - \xi_{ct}$. As a result, district fixed effects from this equation directly recover the district-level 'prison visit' probabilities.

best possible fit. This motivates defining $\mathcal{S} = \mathcal{S}^k + \mathcal{S}^\ell + \mathcal{S}^h$, and choosing the vectors $(\mathbf{q}^\ell, \mathbf{q}^h)$ that maximize the fit of equations (8)-(9) over the identified sets $\mathcal{R}(\mathbf{w}_{ct})$ for each observation:

$$\min_{(\mathbf{q}^\ell, \mathbf{q}^h) \in \times_{ct} \mathcal{R}(\mathbf{w}_{ct})} \mathcal{S}(\mathbf{q}^\ell, \mathbf{q}^h; \mathbf{W}, \mathbf{X}) \tag{11}$$

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 $\mathcal{R}(\mathbf{w}_{ct})$. We implement this procedure separately for minor and serious offenses, effectively allowing both the federal and the local levels to choose different intensities of immigration enforcement along each margin: $(\boldsymbol{\xi}^m, \boldsymbol{\xi}^s)$ and $(\boldsymbol{\epsilon}^m, \boldsymbol{\epsilon}^s)$.[16] We also recover the implied immigration enforcement probabilities for minor and serious offense cases $\boldsymbol{\theta}_m$, $\boldsymbol{\theta}_s$, the corresponding strengths of covariation between these probabilities –$(\kappa_\epsilon^m, \kappa_\xi^m, \gamma^{\ell,m}, \gamma^{h,m})$ and $(\kappa_\epsilon^s, \kappa_\xi^s, \gamma^{\ell,s}, \gamma^{h,s})$–, and 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. A plot of the $\epsilon_{ct}$'s on the $\xi_{ct}$'s over time for a given county reveals the shape of the county's response to the federal effort.

Our ability to go from the partial identification result in Proposition 1 to the point identification result from the solution to (11) relies on two features of (6)-(9): 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 restriction implied by the homogeneous coefficients on county characteristics in these equa-

[16] We use a particle swarm optimizer to minimize equation (11), which is ideal for optimizing a high-dimensional function inside a bounded support.

tions. 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 (11).

# 6 Estimation results

We now present our main findings. First we evaluate the impact of the 2011 change in federal guidelines on federal enforcement preferences and on the number and composition of removals. In doing so, we uncover the nature of the strategic relationship between federal and local enforcement as well as the empirical correlation between federal enforcement efforts and federal-local preference alignment. Second, we assess how the immigration courts' discretion and formal dependence on the executive branch shape the distribution of deportations.

## 6.1 Results: Enforcement probabilities and model fit

Our empirical strategy 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 limits the external validity of our findings. The sample of observations with positive counts of ICE custodies with and without detainers is composed of counties with relatively large populations, and relatively large populations of unlawfully present immigrants. Our results are not representative of the smaller, more rural communities in the US.[17] In Appendix Table B.5 we

[17] In panel B of Table B.3 we report summary statistics for the resulting sample of county-periods with data satisfying the conditions required for identification. Figure B.4 presents a county-level map of the US, where we highlight the counties included in this sample. The

report summary statistics for the data moments $\mathbf{w}_{ct}$ in our estimation sample. On average, transition rates are lower after the 2011 guidelines change at every stage along the pipeline, except for minor offenses in the direct track. Surprisingly, these 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.

In panel A of Table 1 we present average estimates of the model's conditional probabilities by type of offense and period. Panel B reports the estimated coefficients from equations (8) and (9) capturing the covariation between local and federal enforcement along the detainer and direct tracks, and between federal efforts and immigration court outcomes.[18] 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 in the case of minor offenses, they are smaller than the guidelines themselves suggested. For serious offenses, we find a large change in the average rate of compliance with detainers, $g$, which fell by 11 percentage points. We also estimate falls in average preference alignment $\pi^{Hh}/\pi^{H\ell}$ for both levels of offenses, with an *especially large fall* for serious ones.[19] Thus, the fall in detainer issuances and deportations for

map reveals a wide regional coverage. As expected, Texas, Florida, the Southwestern US and the Northeast are heavily represented in our estimation sample.

[18]In Table B.6 and Table B.7 we report the corresponding estimates of the $\boldsymbol{\beta}$ coefficients in equations (6)-(9). Our inference for the coefficients in these equations accounts for the presence of $\epsilon$ and $\xi$ as generated regressors. We present the derivation of these analytic standard errors in Appendix A.3.

[19]Before 2011, we estimate that on average, for every three serious cases of disagreement

minor offenses following the change in guidelines was mostly driven by relaxed federal efforts. In sharp contrast, for serious offenses cases it was driven by an offsetting response of the local level to increased federal efforts, and a concomitant increase in conflict between levels.

The fall over time in preference alignment over serious offenses was partly driven by ICE's change in removal priorities related to offense severity: some types of cases arousing little interest to ICE and over which there was not much local-federal disagreement pre-2011 became of higher interest under the new guidelines, resulting in a divergence in preferences over them. Table 1 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.

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

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between the local and federal levels there is one case over which they agree ($\pi^{Hh}/\pi^{H\ell} = 0.35$). The ratio is even lower post-2011, when it is only one agreement for every four disagreement cases ($\pi^{Hh}/\pi^{H\ell} = 0.23$). Although at the average these may seem surprisingly low levels of agreement, particularly as they involve serious offenses cases, there is considerable variation around this mean: both before and after 2011, the standard deviation of preference alignment across counties and semesters is three times the mean. Moreover, such stark disagreement is consistent with the political backlash that the Secure Communities program experienced, particularly in the most populous counties which our sample mostly represents.

preferences: at the mean, $q^h > q^\ell$. We find, however, that $\xi$ leads to a negative covariation between $f$ and $q^h$, and to a positive covariation between $f$ and $q^\ell$: when federal enforcement was high, the courts moved towards making more likely the removal of individuals the local level would rather not deport.

**Model fit.** We gauge the goodness of fit of our model in Table B.8, comparing the predicted and observed enforcement probabilities of two moments: the probability of a removal conditional on ICE custody and detainer, and the probability of a removal conditional on ICE custody and no detainer. Predicted and observed mean and median probabilities of removal are very similar to each other for both minor and serious crimes, and both before and after the 2011 policy change.

## 6.2 The 2011 ICE guidelines: impact on federal preferences

The 2011 guidelines partly induced a recomposition of the pool of immigrants entering the immigration enforcement pipeline (selection), and party reflected a change in ICE's preferences over different types of unlawful immigration cases. Relying on the measures of preference alignment $(\pi^{Hh}/\pi^{H\ell})_{ct}$ we recovered for each county-semester, we can assess how ICE's preferences over observable case characteristics (national origin and detailed type of offense), changed in response to the new guidelines. This exercise further allows us to draw some indirect welfare implications of the policy change for two reasons: i) under current US law, national origin alone should not be a reason for unequal treatment; ii) despite federal-local disagreement over deportation outcomes, both levels deem cases involving more severe offenses as more amenable to deportation.

In Table 2 we estimate county fixed-effects regressions of $\log(\pi^{Hh}/\pi^{H\ell})_{ct}$ for minor and serious offenses on the composition of the pool of immigrants by national origin and offense category and their interaction with the post-guidelines dummy. Other than county and semester fixed effects, we include key county demographics (the Democratic vote share, the Hispanic share, and the share with a bachelor's degree) interacted with the post-guidelines dummy to control for changes in preferences driven by the overall social environment. Because we can control for the composition of the pool in each county-semester, and under the plausible assumption that county-level preferences over immigrant characteristics did not change at the time of the introduction of the new federal guidelines, we can interpret the guidelines dummy as indicating a 'regime change' of federal preferences $H$: the interaction with with the post-guidelines dummy captures the differential response of our measure of preference alignment to changes in the county's pipeline composition, holding the composition itself constant.

In columns 1 and 3 we consider how federal priorities changed in relation to national origin. We do this including the share of cases of Mexicans and Central Americans, and their interaction with the post-guidelines dummy.[20] For both minor and serious offenses, larger shares of Central Americans in the pipeline are associated with significantly more conflict between levels. This pattern remained unaltered after the change in guidelines, suggesting i) that Central Americans entering the pipeline had characteristics making them relatively unattractive targets of deportation from the perspective of the average county, and ii) that the guidelines did not significantly alter the sharp mis-alignment of preferences over Central Americans between federal and local levels. In contrast, the new guidelines led to increased

[20]All other nationalities constitute the omitted category. During our period of study, Mexicans and Central Americans constitute the bulk of unlawfully present immigrants (65 and 18 percent of all detainers), with the fraction of cases of Central Americans growing over time.

conflict around cases of Mexican nationals accused of minor offenses. Quantitatively, a one standard deviation increase in the share of cases of Mexican immigrants convicted of a minor offense is associated with a 0.13 standard deviations increase in log misalignment in the post-guidelines period.[21] These results are particularly informative about the change in federal preferences because throughout our period of analysis (2010-2015), Mexican and Central American net immigration to the US was effectively zero (see Orozco (2018)).

In columns 2 and 4 we then consider how federal priorities changed in relation to the composition of cases by type of crime. For cases classified as minor, we group them into drug possession charges (5% of all cases), traffic violations (17%), no known convictions (60%), and other (18%).[22] In column 2 we include the shares of each of these categories and their interaction with the post-guidelines dummy. Following the change in federal guidelines, local-federal conflict becomes significantly more responsive to the presence of drug possession and traffic violation cases. The re-direction of priorities away from minor offenses implies the average county would have preferred higher post-guidelines levels of federal enforcement over drug possession and traffic violation cases, which is not too surprising as these are the more serious types of minor offenses.

In column 4 we consider serious offenses, classified into: smuggling –of aliens or narcotics– (20% of cases), assaults (45%), burglaries (33%), and other (2%). We leave the share of burglaries as the omitted category. The new federal guidelines led to large changes in preference alignment between the federal and local levels. Prior to the change in guidelines, semesters

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[21] $0.13 = (-2.27 \times 0.23)/3.97$ 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.

[22] *Other* includes various infrequent offenses. No known convictions is the omitted category.

where the pool of cases had relatively more of the most serious ones (smuggling and assaults), were associated with increased alignment. A one standard deviation increase in the share of smuggling cases is associated with a 0.17 standard deviations increase in log alignment during the pre-guidelines period.[23] Thus, in the typical drug smuggling case for which ICE was pursuing a removal, the county was likely in agreement. Post-guidelines preference alignment is still higher in periods with more smuggling and assault cases, but the relationship is much weaker. This suggests the increased federal attention towards serious offenses was heavily directed towards marginal cases which the local level was less amenable to remove.

### 6.3 The 2011 ICE Guidelines: impact along the pipeline

Besides a change in preferences, the 2011 guidelines also changed how the federal level targeted its enforcement. Within our framework, this represents a change in the underlying relationship between the composition of the pool, $\pi^{Hh}/\pi^{H\ell}$, and federal efforts, $\xi$, at the time of the policy change. Here we assess the impact of the change in federal efforts driven by the new guidelines on the number and composition of removals by considering a counterfactual scenario where the composition of the pool of immigrants entering the pipeline remains as it was before the policy change, thus holding selection constant. To do this, first we use the recovered alignments and federal efforts in the pre and post-guidelines semesters to estimate counterfactual federal efforts under each policy regime, had the composition of the pool been the one in the semester before the policy change. Second, using our estimates of federal and local efforts for each county, we estimate what we refer to as each county's 'best response' slope (i.e., holding the

[23] $0.17 = (9.2 \times 0.14)/7.52$ 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.

composition of the arrest pool constant, by how much do local efforts change as federal efforts vary). We then use the estimated counterfactual federal efforts from the first step to estimate counterfactual local efforts predicted by these best responses. With counterfactual federal and local efforts in hand we then compute conditional immigration enforcement probabilities along the pipeline, holding $\pi^{Hh}/\pi^{H\ell}$ fixed at its value in the semester before the policy change.

**Preference alignment and federal efforts.** Our measure of preference alignment, $\pi^{Hh}/\pi^{H\ell}$, is strongly positively correlated with federal efforts $\xi$. We illustrate this in Figure 3 where we plot the unconditional scatterplots between both variables for both minor (panel a) and serious offenses cases (panel b). We confirm the robustness of this correlation in the first three columns of Table B.9. 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. This is a key finding from 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 remained a key immigration enforcement gatekeeper.

**Best responses.** Because our approach allows us to recover $\xi$ and $\epsilon$ 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 B.10 we present our main estimates of the average slope of this best response across counties for both levels of offenses, in models where we regress $\epsilon$ on $\xi$. We find strategic substitutabilities in both cases, but larger responses for minor offenses. Even columns in the table report county fixed effects models, which 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 1.2 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 that our strategy allows us to distinguish selection from enforcement. In the odd columns of the table we report the results of a pooled regression of $\epsilon$ on $\xi$, allowing us to assess the validity of our claim. In the pooled model, county-level fixed effects are in the residual. For both levels of offenses, the pooled and fixed effects coefficients are similar, showing that $\xi$ is uncorrelated with fixed county-level unobservables. These results motivate us to show in Figure B.5 the scatterplots corresponding to the pooled regressions, where we distinguish between counties above (blue) and below (red) median Democratic vote share.

We expect counties with different preferences to respond differently to federal enforcement. How much heterogeneity is there in the nature of the local-level enforcement response? Figure B.6 plots the county-level distribution of slopes, which we recover directly from linearly fitting $\epsilon$ to $\xi$ county by county. For both minor and serious offenses cases, around 80 percent of counties exhibit negative slopes, indicating strategic substitutability. The other 20 percent show positive slopes, indicating strategic complementarity.

To investigate the main drivers of the heterogeneity in best response slopes, in Table 3 we present results of cross-sectional regressions for the slopes of each county's best response on county characteristics related to local preferences over immigration policy. In columns 1 and 4 we include a constant and the Democratic vote share ($-50$ percent). More Democratic counties exhibit significantly more negative best responses for serious offenses. In columns 2 and 5 we then add the Hispanic population share. 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, log population, the share with a bachelor's degree, a rural county dummy, the share of employment in services, log distance to ICE and a 287(g) cooperation agreement dummy. The inclusion of these controls leads to a negative coefficient on the Democratic share 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. 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.[24]

**Counterfactual exercise: no selection effects after the change in guidelines.** We are now ready to isolate the effect of enforcement under the guidelines, by considering a contrasting counterfactual scenario that holds preference alignment (i.e., the pool composition) constant. First, we estimate the average relationship between federal efforts and preference alignment across counties in the pre-guidelines period regressing $\xi_{ct}$ on $\log(\pi^{Hh}/\pi^{H\ell})_{ct}$ (using

[24] As a robustness exercise, we re-estimated the full model on the sub-sample of county-semesters common to the minor and serious offenses samples. Results are qualitatively similar to the ones discussed here. We present a summary of those results in Appendix Tables B.11 and B.12 and Appendix Figures B.7 and B.8.

the black fit line in Figure 3). We evaluate this conditional mean function at the preference alignment we recovered for the last period available before the new guidelines were introduced (first semester of 2011 in most cases), which we refer to as $(\pi^{Hh}/\pi^{H\ell})_{c0}$, to obtain a predicted federal enforcement effort $\hat{\xi}_c^{pre}$. We follow analogous steps for the post-guidelines period, and obtain a predicted federal enforcement effort $\hat{\xi}_c^{post}$ (using the gray fit line in Figure 3). These are, respectively, the best predictions for federal enforcement under the pre and post-guidelines regimes, had the pool composition been held fixed at the 2011-1 level. Second, we evaluate the recovered best responses for each county at these counterfactual federal efforts, to obtain the predicted local enforcement efforts $\hat{\epsilon}_c^{pre}$ and $\hat{\epsilon}_c^{post}$ that would have been observed in response to these federal efforts. Armed with these counterfactual local and federal efforts, and using our parameter estimates, we recover the implied pre and post 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 using equations (1)-(5).

We compute the counterfactual percent difference in number of deportations between both scenarios for each county-time period following the change in guidelines.[25] Figure 4 plots the resulting distributions of percent differences for minor and serious offenses cases, across county-time periods after 2011-II. Under the new guidelines, but holding fixed any effects the policy may have had over the composition of the arrest pool, the median county-semester would have experienced 1.1 percent less removals for minor offenses cases. It would have experienced 164 percent more removals for serious ones.[26] There is considerable variation

[25] As we show in Appendix A.4, this quantity is identified.

[26] Mean counterfactual vs. predicted differences are -2% (minor) and 189% (serious).

across county-time periods in the outcomes of this comparison, however. While only 38 percent of county-semesters would have experienced more minor offense removals, 78 percent would have experienced more serious offense removals in the absence of changes in the pool composition. Two thirds of county-semesters would have observed removals to be more than 50 percent higher. We can conclude that the spirit of the guidelines was followed: federal efforts towards minor offenses were reduced slightly, and redirected and magnified towards serious offenses. As a corollary, the puzzling fall in the raw number of observed deportations for serious offenses we highlighted in the introduction was driven by a drastic recomposition of the pool of arrested immigrants, and not to lack of compliance with the 2011 guidelines by ICE agents. Note that in the absence of changes in the pool composition, the countervailing (for most counties) enforcement response of the local level to federal efforts would not have been enough to reduce deportations for serious offenses.

### 6.4 The immigration courts

Immigration courts constitute the last step of the immigration enforcement pipeline. They are the institutions 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.

**Secession from the executive branch.** Immigration courts in the US are under the jurisdiction of the Department of Justice, and as such, are part of the federal executive branch. Our model allowed for a dependence between federal enforcement efforts and the conditional probabilities of removal at the court stage to capture this institutional feature: in equation (9), $\gamma^{\tau}$ indicates how, on average, courts change the likelihood of removing type

$\tau \in \{\ell, h\}$ unlawfully present immigrants as the federal level's enforcement effort $\xi_{ct}$ varies, holding constant the composition of unlawfully present immigrants entering the pipeline. We model immigration courts not being under the jurisdiction of the executive 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.

We can simulate the percent difference in removals between this counterfactual scenario and the baseline model predictions for each county semester. We present the main results of this exercise in Table 4 under the row labeled 'Courts secede'. Our estimate of $\gamma^{\ell}$ is positive, while our estimate of $\gamma^{h}$ is negative (see Table 1) for both minor and serious offenses. On average courts reinforced ICE efforts when the pool contained more $\ell$ 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 recovered federal efforts. Figure B.9 plots the full distribution of counterfactual percent changes. Across the distribution of county-semesters, 61 percent would observe higher removals of minor offenses cases under seceded courts that under the baseline. The median county-semester would experience a 1.2 percent higher number of removals. Aggregating over all county-semesters, seceded courts would lead to only a 0.8 percent higher number of removals. Looking at serious offenses cases, 68 percent of county-semesters would observe higher removals under seceded courts that under the baseline. The median county-semester would experience a 3.2 percent higher number of removals. Finally, aggregating over all county-semesters, seceded courts would lead to a 5.5 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.[27]

**Homogenization of immigration court severity.** Discretion (courts making dissimilar decisions on observably similar cases) is another salient institutional feature of the immigration court system. Conditional on county characteristics $\mathbf{x}_c$ and federal efforts $\xi_{ct}$, in our model the residual variation in removals at the court stage is captured by $\zeta_{ct}^{\tau}$, the residuals from equation (9). How would the distribution of removals across county-semesters change if, conditional on observables, all immigration courts were equally lenient or equally harsh? We provide an answer to this question with an exercise where we use the distribution of estimated $\zeta_{ct}^{\tau}$'s to simulate the resulting percent difference in removals between the counterfactual and the baseline predictions from assigning to every county-semester the same value of $\zeta_{ct}^{\tau}$. We explore three possibilities: i) very lenient courts, where we use the 10th percentile of the distribution of $\zeta_{ct}^{\tau}$; ii) median-leniency courts, where we use the 50th percentile; and iii) harsh courts, where we use the 90th percentile.

The results of these exercises appear in Table 4 on the rows labeled 'Courts severity ho-

[27] 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.13. Among types of minor offenses, removals of cases involving traffic violations would be 1.4 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 5.7 percent, while those involving assaults would increase by 2.5 percent. Looking at demographics, removals of Central American nationals would increase by 6.5 percent, while removals of Mexican nationals would increase by 4.7 percent.

mogenized'. The corresponding distributions of percent changes and additional results by case characteristics appear in Figure B.10 and Table B.13. The aggregate number of removals for minor offenses across all county-time periods would be 38 percent lower if we moved all courts to the 10th percentile of the distribution of $\zeta_{ct}^{\tau}$. They would be 1.4 percent higher if all courts were at the median, and 27.5 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 24.7 percent lower at the 10th percentile, 2.8 percent higher at the median, and 28.7 percent higher at the 90th percentile. Under the extreme leniency counterfactual, removals involving minor offenses such as drug possession and traffic violations would exhibit larger aggregate percent falls (around 40 percent reductions), while removals of cases involving serious offenses such as drug smuggling and assault would fall by 18 to 26 percent (see Table B.13). This suggests that courts exercise more discretion on relatively less serious cases.

Collapsing all idiosyncratic variation in court behavior to a mass point is not feasible (and perhaps not desirable). Because the estimated changes we describe here hold constant the composition of the arrest pool, however, the exercise highlights that policies intended to reduce 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 plays a key role in explaining the pattern of deportations under the Secure Communities program.

### 6.5 Model validation

We complement our analysis with three implicit specification tests of our model.

**Enforcement probabilities.** First, an internal validity check: in Table B.14 we show that the fit of our benchmark equations for $k, q^\ell, q^h$ in (8) and (9), which depend on local and federal efforts as regressors, improves considerably when including these efforts as predictors compared to models that exclude them. For $k$ along the serious offenses pipeline, for example, the $R^2$ jumps from 6 percent when only including county characteristics $\mathbf{x}$, to 87 percent when including both $\epsilon$ and $\xi$. We observe similar increases across all equations.

**Local efforts and preference alignment.** Second, we show that local efforts and preference alignment are not correlated controlling for federal efforts. Our measure of the local-level willingness to collaborate with the federal level over $\ell$-type cases is captured by $\epsilon$. Thus, any unconditional correlation between local efforts $\epsilon$ and preference alignment $\pi^{Hh}/\pi^{H\ell}$ should disappear conditional on the federal-level effort $\xi$: local efforts should not vary with the composition of the pool other than through their variation in response to the federal efforts $\xi$. In column 4 of Table B.9 we report the regression coefficients for the unconditional relationship between $\epsilon$ and $\pi^{Hh}/\pi^{H\ell}$ for both minor and serious offenses. Because, as we illustrated above, $\xi$ and $\pi^{Hh}/\pi^{H\ell}$ are strongly positively correlated and most counties exhibit strategic substitutabilities, naturally the unconditional correlation between local efforts and preference alignment is strong and negative. This is also the case after introducing county fixed effects in columns 5-6. In columns 7-9 controlling for federal efforts $\xi$, however, the negative relationship between local efforts and preference alignment vanishes. This exercise reassures us that the estimated best responses can be interpreted causally, and that our model of the pipeline is a good approximation to the actual operation of the process.

**The California Trust Act.** Third, we show that our measure of local enforcement efforts behaves as expected when looking at the effects of another policy: the California Trust Act.

This state law came into effect on January 2014, imposing limits on local-level collaboration with ICE detainer requests. Under the Trust Act, police are only allowed to honor detainers falling into a specific list of relatively serious offenses. 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 5 presents the evolution of the median of our estimated local immigration enforcement efforts $\hat{\epsilon}_{ct}$, distinguishing between California counties (in solid black) and all other counties (in dotted gray). The vertical line indicates the activation of the Trust Act. In panel (a) we see that local efforts over minor offenses cases fell 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 these cases, California counties followed the same trend as the rest of the US. These results illustrate that our model captures accurately the realized patterns of immigration enforcement under Secure Communities.

# 7 Concluding Remarks

We study immigration enforcement under the Secure Communities program, focusing on the interaction between local and federal levels. We find evidence of strategic substitutabilities in the response of the local level to changes in federal immigration enforcement, particularly among the most Democratic counties. We also find that ICE is effective at directing its enforcement efforts towards counties where it expects local collaboration (possibly because of the informational advantage it acquired under Secure Communities). Most of the reduction in deportations following a change in prosecutorial priorities at the federal level in 2011 can be attributed to a change in the composition of the pool of immigrants entering the deportation pipeline, particularly for cases related to serious offenses, and not to a reduction in federal enforcement. We also quantify the importance of discretion and dependence on the executive branch –two key institutional features of the immigration courts system–, on the number and composition of removals. 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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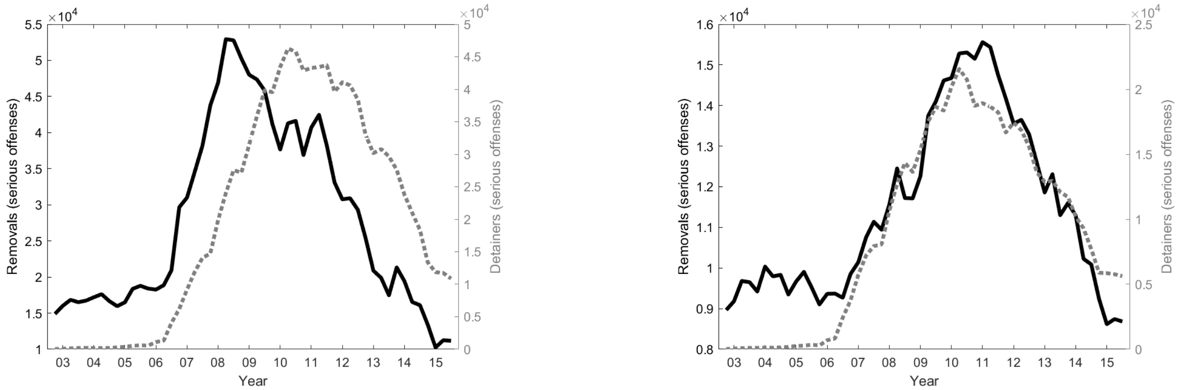
# Figures and tables




**(a)** Minor offenses

**(b)** Serious offenses

**Figure 1: Detainers and removals, 2003-2015.** Figure (a) shows the aggregate number of detainers issued (dotted gray) and removals (solid black) for arrestees charged with minor offenses. Figure (b) shows the aggregate number of detainers issued (dotted gray) and removals (solid black) for arrestees charged with serious offenses. Data are aggregated at the quarterly level. Source: TRAC.

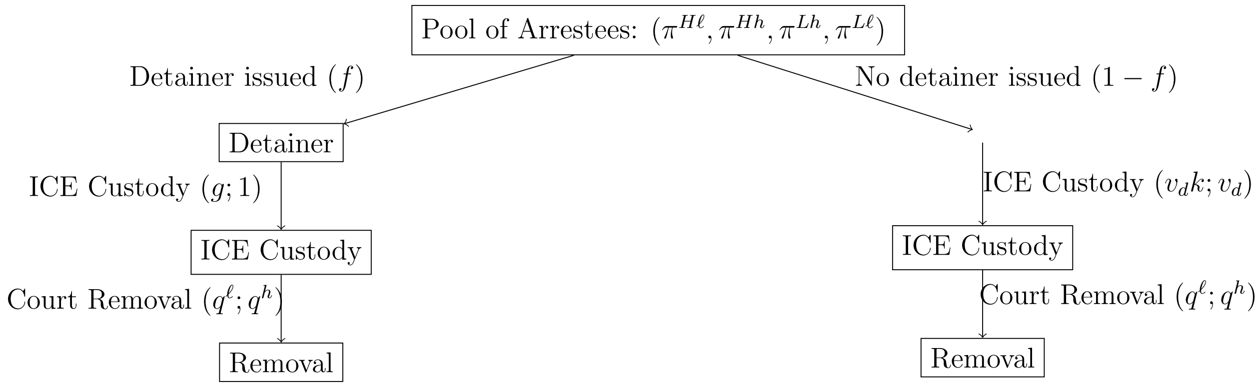
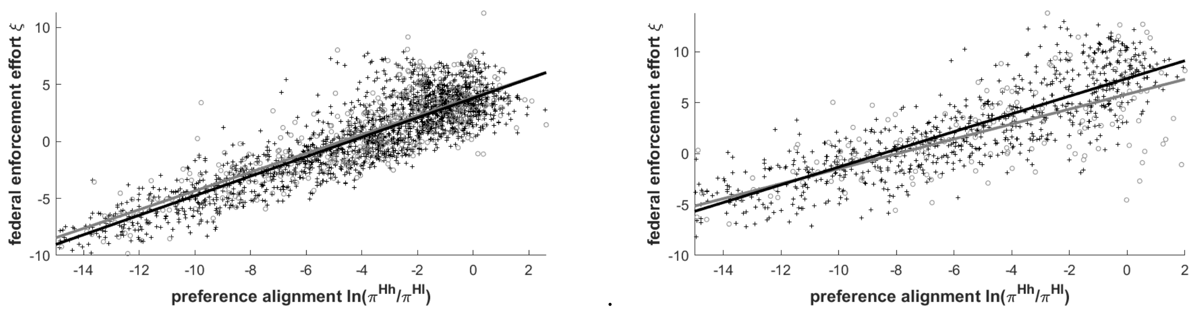


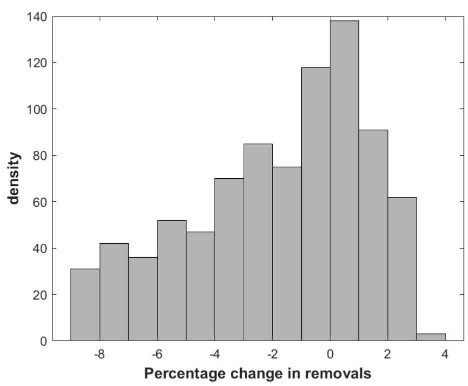

**Figure 2: The immigration enforcement pipeline.** The figure shows a flow chart of the immigration enforcement pipeline, with its detainer track (left side), and its direct track (right side). $L$ and $H$ represent low and high priority arrestees for ICE. $\ell$ and $h$ represent low and high priority arrestees for the local level. The $\pi$'s represent the shares of each type in the population of arrestees. $f$ is the probability of detainer issuance by ICE, $g$ is the probability of ICE custody following a detainer, $k$ is the probability of ICE custody in the absence of a detainer, and $q^\ell, q^h$ are the probabilities of removal for $H\ell$ and $Hh$ type arrestees in ICE custody.



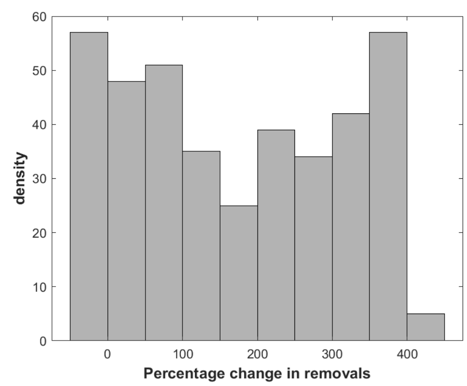

**(a)** Minor offenses

**(b)** Serious offenses

**Figure 3: 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 B.9. 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 B.9. Black represent periods before the guidelines change. Gray represent the periods after the guidelines change.

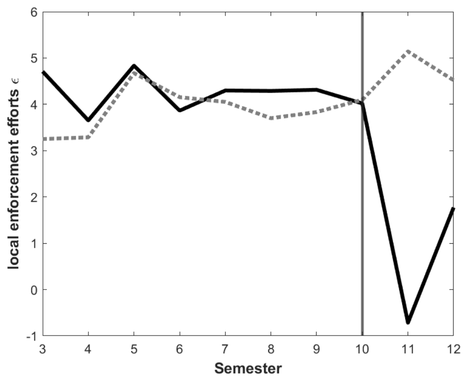



**(a)** Minor offenses

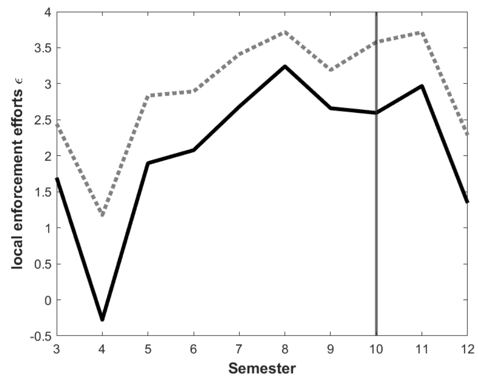



**(b)** Serious offenses

**Figure 4: Counterfactual changes in removals: pre vs post guidelines regimes.** Panel (a) presents a histogram of the distribution across county-time periods of counterfactual pre-post percent changes in removals for minor (levels 2-4) offenses, holding selection constant. Panel (b) presents a histogram of the distribution across county-time periods of counterfactual pre-post percent changes in removals for serious (level 1) offenses, holding selection constant.




**(a)** Minor offenses




**(b)** Serious offenses

**Figure 5: 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 $\epsilon$ across counties. The black solid line depicts the median for California counties. The gray dotted line depicts the median for all other US counties. The vertical 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.

| 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. |
| $f \equiv \mathbb{P}(\text{Detainer})$ | 0.24 | 0.30 | 0.03 | 0.08 | 0.21 | 0.27 | 0.12 | 0.24 |
| $g \equiv \mathbb{P}(\text{ICE Custody}\|\text{Detainer}, \ell)$ | 0.28 | 0.26 | 0.54 | 0.31 | 0.26 | 0.27 | 0.43 | 0.29 |
| $q^l \equiv \mathbb{P}(\text{Removal}\|\text{Custody}, \text{Detainer}, \ell)$ | 0.52 | 0.31 | 0.44 | 0.31 | 0.57 | 0.29 | 0.49 | 0.27 |
| $q^h \equiv \mathbb{P}(\text{Removal}\|\text{Custody}, \text{Detainer}, h)$ | 0.69 | 0.28 | 0.72 | 0.27 | 0.68 | 0.25 | 0.73 | 0.27 |
| $v^d \equiv \mathbb{P}(\text{Custody}\|\text{No Detainer}, h)$ | 2.33 | 2.51 | 0.26 | 0.33 | 1.47 | 2.37 | 1.63 | 2.33 |
| $k \propto \mathbb{P}(\text{ICE Custody}\|\text{No Detainer}, \ell)$ | 0.16 | 0.33 | 0.07 | 0.23 | 0.22 | 0.36 | 0.13 | 0.31 |
| $\pi^{Hh}/\pi^{H\ell}$ = preference alignment | 0.33 | 0.97 | 0.35 | 0.99 | 0.30 | 0.68 | 0.23 | 0.69 |
| Observations | 448 | | 189 | | 1,900 | | 912 | |

| Panel B: | Coefficients on Enforcement Efforts | | | |
|---|---|---|---|---|
| Dependence between | Minor Offenses | | Serious Offenses | |
| local effort and $k$: $\kappa_\epsilon$ | -0.27 | (0.016) | -0.27 | (0.034) |
| federal effort and $k$: $\kappa_\xi$ | 0.99 | (0.045) | 0.95 | (0.039) |
| federal effort and $q^\ell$: $\gamma^l$ | 0.23 | (0.048) | 0.11 | (0.045) |

| | | | | |
|---|---|---|---|---|
| federal effort and $q^h$: $\gamma^h$ | -0.18 | (0.043) | -0.27 | (0.030) |
| Observations | 2,348 | | 1,101 | |

**Table 1: 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 (8) and (9), for minor and serious offenses. Standard errors for these coefficients, reported in parentheses, account for the presence of generated regressors in equations (8) and (9) (see subsection A.3).

| | Dependent Variable: Preference Alignment $\text{Log}(\pi^{Hh}/\pi^{H\ell})_{ct}$ | | | | |
|---|---|---|---|---|---|
| | Minor Offenses | | | Serious Offenses | |
| | (1) | (2) | | (3) | (4) |
| National origin | | | | | |
| Mexican$_{ct}$ | -0.52 | | | -3.00 | |
| | (1.03) | | | (1.84) | |
| $\times$Guidelines$_t$ | -2.27 | | | -2.19 | |
| | (1.00) | | | (1.58) | |
| Central American$_{ct}$ | -4.83 | | | -9.03 | |
| | (1.30) | | | (2.86) | |
| $\times$Guidelines$_t$ | -0.64 | | | -0.03 | |
| | (1.22) | | | (2.71) | |
| Minor | | | Serious | | |
| Drug possession$_{ct}$ | | -1.46 | Smuggling$_{ct}$ | | 9.20 |
| | | (2.45) | | | (2.58) |
| $\times$Guidelines$_t$ | | -4.67 | $\times$Guidelines$_t$ | | -8.09 |
| | | (2.47) | | | (2.63) |
| Traffic violation$_{ct}$ | | 0.41 | Assault$_{ct}$ | | 8.38 |
| | | (1.07) | | | (2.47) |
| $\times$Guidelines$_t$ | | -7.01 | $\times$Guidelines$_t$ | | -6.89 |
| | | (1.09) | | | (2.61) |
| Other$_{ct}$ | | -6.42 | Other$_{ct}$ | | 8.56 |

| | | | | | |
|---|---|---|---|---|---|
| | | (1.24) | | | (9.44) |
| $\times$Guidelines$_t$ | | 2.01 | $\times$Guidelines$_t$ | | -21.01 |
| | | (1.22) | | | (10.56) |
| R squared | 0.03 | 0.05 | | 0.05 | 0.04 |
| Observations | 2,347 | 2,347 | | 1,095 | 1,095 |

**Table 2: Preference alignment and observable case characteristics.** The table reports coefficients for county fixed effects models. The dependent variable is log of preference alignment $\pi^{Hh}/\pi^{Hl}$, for minor (columns 1-2), and serious offenses cases (columns 3-4). Each observation corresponds to a county-semester. Control regressors include: county and semester fixed effects, and county characteristics interacted with the policy change (omitted from the table): 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. Guidelines is a dummy variable indicating the semesters after the guidelines change. The key explanatory variables are time varying case-specific characteristics). Columns 1 and 3 include the fractions of detainers issued against immigrants by national origin in the county-semester, and their interaction with the Guidelines dummy. The omitted category is all other nationalities. Columns 2 and 4 include the fractions of detainers issued against immigrants by sub-type of offense in the county-semester, and their interaction with the Guidelines dummy. 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. Smuggling includes drug trafficking and the smuggling of aliens. Standard errors are robust to arbitrary heteroskedasticity.

| Dependent Variable: County's Best Response Slope | | | | | | |
|---|---|---|---|---|---|---|
| | Minor Offenses | | | Serious Offenses | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | -1.87 | -2.12 | -3.95 | -0.70 | -0.68 | -2.38 |
| | (0.07) | (0.10) | (1.34) | (0.06) | (0.09) | (1.31) |
| Democratic party share | 0.07 | -0.04 | -1.14 | -1.76 | -1.75 | -1.83 |
| | (0.43) | (0.43) | (0.58) | (0.37) | (0.38) | (0.53) |
| Hispanic share | | 1.45 | 1.78 | | -0.12 | -0.16 |
| | | (0.42) | (0.54) | | (0.33) | (0.43) |
| Undocumented share | | | -1.64 | | | 10.17 |
| | | | (4.10) | | | (4.02) |
| Log population | | | 0.25 | | | 0.09 |
| | | | (0.09) | | | (0.08) |
| Bachelor degree share | | | 1.42 | | | 0.80 |
| | | | (0.91) | | | (0.80) |
| Rural | | | -0.58 | | | -0.25 |
| | | | (0.25) | | | (0.33) |
| Services share | | | -2.66 | | | -0.17 |
| | | | (1.44) | | | (1.36) |
| Log distance ICE office | | | 0.001 | | | 0.04 |
| | | | (0.02) | | | (0.02) |
| 287(g) program | | | 0.22 | | | 0.22 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | (0.23) | | | (0.18) |
| R squared | 0.0002 | 0.01 | 0.05 | 0.03 | 0.03 | 0.06 |
| Observations | | 429 | | | 201 | |

**Table 3: Heterogeneity in local best responses.** The table shows regression coefficients for the slopes of the best response of $\epsilon$ to $\xi$, for minor and serious offenses. The dependent variable in all specifications is the slope of a regression of $\epsilon$ on $\xi$ 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).

| | Minor Offenses | | | Serious Offenses | | |
|---|---|---|---|---|---|---|
| | Median | Positive change | Aggregate | Median | Positive change | Aggregate |
| Courts secede | 1.2% | 60.7% | 0.8% | 3.2% | 67.9% | 5.5% |
| Courts severity homogenized | | | | | | |
| 10th percentile | -46.0% | 4.0% | -38.0% | -31.4% | 6.0% | -24.7% |
| 50th percentile | 1.0% | 52.3% | 1.4% | 2.0% | 52.9% | 2.8% |
| 90th percentile | 32.0% | 93.7% | 27.5% | 32.6% | 91.6% | 28.7% |
| Observations | 2,348 | 2,348 | 2,348 | 1,101 | 1,101 | 1,101 |

**Table 4: 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.4. 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.