Trade Effects of Immigration Enforcement*

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Abstract

Economists have long emphasized that labor market institutions and policies influence comparative advantage by shaping employment conditions and production costs. By contrast, little is known about how direct shocks to labor endowments affect comparative advantage and trade patterns. This paper examines the effects of U.S. interior immigration enforcement, a major policy intervention that reduces the supply of low-skilled labor, on domestic and international trade flows in a highly labor-intensive sector. I focus on the fruit and vegetable industry, where production depends heavily on foreign-born workers, nearly half of whom lack legal status. Exploiting spatiotemporal variation in enforcement intensity between 1997 and 2012, I find that stricter enforcement reduces fruit and vegetable production, lowers interstate exports, and increases interstate and foreign imports. International exports display negative point estimates but are imprecisely estimated. Robustness checks confirm that these results are not driven by worker inflows from other states or pre-trends.

Keywords: Immigration enforcement, comparative advantage, labor market shocks, agricultural labor markets, international trade, domestic trade

JEL Codes: F14, F16, J43, K37, Q17

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1 Introduction

Labor endowments remain central to theories of comparative advantage. Their surplus or shortage directly affects not only wages and employment but also production capacity, industry structure, and competitiveness. A growing body of research shows how labor market institutions and policies, such as minimum wages, labor standards, and employment protections, alter firm dynamics, productivity, and exporting behavior by influencing unit labor costs and adjustment frictions (Askenazy, 2003; Helpman and Itskhoki, 2010; Cunat and Melitz, 2012; Gan et al., 2016; Fan et al., 2018; Roy, 2021; Muñoz, 2023). Yet, much less is known about how direct shocks to labor endowments themselves, such as sudden contractions in the supply of low-skilled workers, affect comparative advantage and trade outcomes.

One of the most significant U.S. policy interventions affecting low-skilled labor markets over the past two decades has been the intensification of interior immigration enforcement. The Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA) established the institutional framework for enforcement, which expanded sharply after the 9/11 attacks as federal, state, and local authorities expanded their activities. These measures targeted undocumented workers through both policing (local police cooperation and deportations) and employment (employer verification of legal status) channels, and their adoption varied widely across time and jurisdictions. Empirical evidence shows that enforcement reduced the presence of undocumented immigrants by increasing deportations, discouraging new inflows, and pushing migrants toward less strict areas (Bohn et al., 2014; Amuedo-Dorantes et al., 2019; Smith, 2023; East et al., 2023). Despite growing evidence of their effects on local labor markets, their broader implications for trade and competitiveness remain largely unexplored.

This paper examines the effects of U.S. interior immigration enforcement on domestic and international trade flows in a highly labor-intensive sector. I focus on the fruit and vegetable industry, where roughly 70 percent of crop workers are foreign born and nearly half lack legal status (Martin, 2017b). This reliance makes the sector especially vulnerable to enforcement-induced labor shortages, offering a suitable context for investigating this question. Prior studies show that tighter enforcement reduces the availability of farm workers and raises wages, thereby increasing production costs in labor-intensive agriculture (Kostandini et al., 2014; Ifft and Jodlowski, 2022). At the same time, fruit and vegetable trade patterns have shifted dramatically: since 1990, the real value of FV imports has risen nearly ten-fold, while exports have remained relatively flat, generating a trade deficit of about 20 billion dollars by 2022. Imported produce now accounts for roughly 59 percent of fruit consumption and 35 percent of vegetable consumption in the United States (USDA ERS, 2023). These shifts reflect not only labor market pressures but also broader competitive forces, including structural changes in the food industry and competition from low-cost producers (Johnson, 2014), thus suggesting a reallocation of comparative advantage across producers.

To answer this question, I exploit spatial, temporal, and intensity variations of enforcement programs across contiguous U.S. states. I construct a state-by-year enforcement index by aggregating five enforcement policies. I link this policy index to state outcomes from the USDA Census of Agriculture and to bilateral trade flows from FAF-5, which provides consistent interstate and international shipments of fruits and vegetables at five-year intervals. The sample covers 1997 to 2012, ending before major restructuring and changes in the scope of several programs. Trade effects are estimated using a Poisson Pseudo Maximum Likelihood (PPML) gravity framework with high-dimensional fixed effects, state-specific linear trends, and covariates. The import specification symmetrically applies destination enforcement and origin-year fixed effects. The identifying variation comes from within-pair changes in state enforcement intensity over time, conditional on these covariates and fixed effects.

Our results indicate that stricter interior enforcement constrains the supply of hired farm labor. Higher enforcement is associated with lower labor expenditures at the state level, both in absolute terms and as a share of operating costs. The total sales of fruits, nuts, and vegetables declines, consistent with larger harvest losses and lower marketed volumes when crops go unpicked rather than changes in planted acreage. These production adjustments are the key mechanism through which enforcement shocks transmit to trade outcomes: lowering interstate exports, shifting domestic sourcing toward origins with lower enforcement, and increasing imports.

Turning to trade, on the domestic margin, enforcement reduces interstate exports of fruits and vegetables and increases interstate imports. States with higher enforcement export fewer shipments to other states, while simultaneously sourcing more from other domestic suppliers. Importantly, the extent of reallocation depends on the enforcement condition of trading partners. Destination states increase purchases from origins with below-median enforcement and reduce purchases from origins with above-median enforcement. This shows that relative enforcement intensity across trading partners plays a central role in shaping domestic trade patterns.

On the international margin, immigration enforcement is associated with a decline in state-level exports of fruits and vegetables, although these effects are imprecisely estimated. Imports, in contrast, increase in aggregate, indicating a greater reliance on foreign suppliers. Within this broader rise in imports, we also observe significant increases in shipments from Mexico, the largest fruit and vegetable import partner for the United States. In addition, major port states increase imports in response to the intensification of enforcement in their domestic export partner states.

Robustness analyses support the main findings. Controlling for potential inflows of workers displaced from other states due to their enforcement does not alter the results, indicating that domestic trade responses are not driven by relocation of labor. Falsification test using less labor-intensive agricultural commodities yield no systematic effects, confirming that the observed responses are specific to labor-intensive production. Tests for policy endogeneity, including analyses of pre-treatment levels, trends, and lead-years enforcement intensity as the regressor, do not show systematic anticipatory behavior or selection on unobservables. Taken together, the results indicate that immigration enforcement effectively functions as trade policy in labor-intensive agriculture: it constrains labor at the farm level, reduces export capacity, reallocates domestic shipments toward lower-enforcement origins, and increases reliance on foreign imports.

Although the analysis centers on U.S. fruits and vegetables, the mechanisms identified are not confined to agriculture. In many tradable sectors, competitiveness depends heavily on the availability of low-skilled labor. Apparel, meatpacking, hospitality-linked food processing, and certain segments of manufacturing all rely disproportionately on migrant or otherwise elastic labor supplies. The results here suggest a more general principle: restrictive labor market policies can erode comparative advantage in labor-intensive industries by raising production costs and contracting export capacity. Likewise, the buffering role of domestic trade networks observed for agriculture parallels how internal trade reallocates manufacturing goods across regions in response to local shocks. In this sense, the U.S. horticultural sector provides a tractable case study, but the implications extend to broader debates about how labor endowments shape trade flows in large, integrated economies.

This paper contributes to several strands of economic literature. First, it adds to the literature on the effects of labor supply shocks on trade and to broader debates on the determinants of comparative advantage. While most research linking trade and labor markets has focused on how trade shocks affect labor outcomes (Goldberg and Pavcnik, 2007; Topalova, 2010; McCaig, 2011; Autor et al., 2013; Acemoglu et al., 2016; Bloom et al., 2016; Costa et al., 2016; Pierce and Schott, 2016; Pavcnik, 2017), a smaller but growing body of work studies the reverse channel, showing how labor market institutions and shocks influence trade patterns (Askenazy, 2003; Kucera and Sarna, 2006; Helpman and Itskhoki, 2010; Cunat and Melitz, 2012; Gan et al., 2016; Fan et al., 2018; Ni and Kurita, 2020; Roy, 2021; Muñoz, 2023). Within this line, my paper highlights how immigration enforcement alters state-level comparative advantage in labor-intensive agriculture. While prior research has emphasized technology and factor endowments (Costinot, 2009), financial institutions (Svaleryd and Vlachos, 2005; Nunn and Trefler, 2014), market regulations (Costinot, 2009; Santeramo and Lamonaca, 2019), contract enforcement (Levchenko, 2007; Nunn, 2007), labor market rigidity (Helpman and Itskhoki, 2010; Cunat and Melitz, 2012), government support programs (Tong et al., 2019), and innovation (Santacreu, 2015), this study shows that shocks to labor supply, labor-intensive production, and trade outcomes are also deeply interconnected.

Second, it contributes to the growing literature linking immigration shocks and trade. Nearly all studies on this topic focus on positive immigration shocks, which lower transaction costs through migrant networks, improve productivity, and shift comparative advantage by reallocating resources. Empirical evidence shows that immigrant inflows enhance firm performance and export outcomes in manufacturing and services, operating at both the intensive and extensive margins and often propagating through domestic networks (Pennerstorfer, 2016; Cohen et al., 2017; Mitaritonna et al., 2017; Lombardo and Peñaloza-Pacheco, 2021; Akgündüz et al., 2023, 2024; Orefice et al., 2025). Yet far less is known about how restrictive policies and reductions in immigrant labor supply affect trade and competitiveness. Existing studies on U.S. agriculture, such as Zahniser et al. (2012) and Devadoss and Luckstead (2011), analyze how immigration policy affects exports using CGE or bilateral trade models, but they do not examine state-level heterogeneity, interstate trade flows, or import substitution effects, which are central to my analysis.

Third, this paper contributes to the literature on immigration policy. While research has studied the effects of immigration policies on labor market outcomes, both within agriculture (Kostandini et al., 2014; Ifft and Jodlowski, 2022; Luo and Kostandini, 2022, 2023) and beyond (Amuedo-Dorantes and Bansak, 2012; Bohn et al., 2014, 2015; Orrenius and Zavodny, 2015; Pope, 2016; East and Velásquez, 2022; Tran, 2023; East and Velásquez, 2024), there has been little systematic analysis of how they influence trade margins or comparative advantage. By connecting interior enforcement to trade in labor-intensive agriculture, this study fills a gap in understanding the macroeconomic ripple effects of immigration policy that extend beyond labor markets.

Finally, this study offers new insights into the resilience of domestic food systems. While natural factors such as climate determine the baseline geography of production, policies that influence labor availability can be equally important in shaping where and how food is sourced. Immigration enforcement reduces the supply of low-skilled farm labor, constraining output in labor-intensive crops and forcing downstream buyers to adjust sourcing strategies. These adjustments may involve substitution across crops or reallocation of procurement to states with less stringent enforcement. In this way, labor policy can propagate through supply chains in ways that mirror natural shocks, creating vulnerabilities in food security and resilience. By documenting how enforcement reshapes domestic and international trade flows, the paper highlights that resilience is not solely about adapting to environmental risks, but also about managing the consequences of labor market and policy shocks.

The remainder of the paper is organized as follows. Section 2 provides institutional and sectoral background on U.S. agricultural trade, farm labor, and immigration enforcement. Section 3 outlines the theoretical framework. Section 4 describes the data and empirical strategy. Section 5 presents the empirical findings and Section 6 presents robustness checks. Section 7 concludes.

2 Background and Related Literature

2.1 Trade, Factor Endowment, and Agriculture

In trade theory, labor is a central factor endowment shaping comparative advantage. For fruit and vegetables, this link is especially strong because most crops are fragile, perishable, and must be hand-harvested. Mechanization is limited, making fruit and vegetable production highly labor-intensive. Farm labor accounts for about 42 percent of variable production expenses for U.S. Fruits and vegetables (Martin and Calvin, 2011). Rising labor costs therefore directly raise production costs, potentially reducing output and eroding comparative advantage relative to foreign producers.

The 2022 U.S. Agriculture Census reported fruit and vegetable sales of USD 43.7 billion, representing 8 percent of total agricultural output and 16.8 percent of crop production

(USDA NASS, 2024). Over the last two decades, however, production of major Fruits and vegetables in the U.S. has declined while imports have risen dramatically. Agricultural imports from Mexico grew from USD 2.7 billion in 1990 (6.05 billion after inflation) to USD 43.4 billion in 2022, around half of which were Fruits and vegetables (U.S. Department of Commerce, 2023). As shown in Figure 7, total fruit and vegetable imports have increased roughly tenfold since 1990, while exports have remained relatively stable. The fruit and vegetable trade deficit has widened from under USD 1 billion in 1990 to roughly USD 20 billion in 2022. Imported produce now accounts for around 60 percent of fresh fruits and 40 percent of fresh vegetables consumed in the U.S., up from 30 percent and under 10 percent, respectively, in 1981 (Figure 2).

Mexico is the dominant U.S. fruit and vegetable import partner, supplying 58.6 percent of imports in 2022, followed by Canada, Peru, Chile, and Guatemala (Figure 7). U.S. trade with Mexico mirrors overall foreign fruit and vegetable trade patterns (Figure 7). Canada, while a net importer of U.S. Fruits and vegetables, has seen its exports to the U.S. steadily rise since the early 1990s, reaching 8.9 percent of imports in 2022 (Figure 5). Export gains for U.S. producers have been concentrated in berries, apples, peaches, pears, grapes, and leafy greens, while imports have surged in citrus, tropical fruits, berries, and grapes (Johnson, 2014).

Johnson (2014) highlights five factors shaping these dynamics: (1) market shifts such as exchange rates and structural changes in the food industry, (2) increased competition from low-cost or subsidized producers abroad, (3) an open domestic import regime with low tariffs and preferential trade agreements, (4) persistent non-tariff barriers to U.S. exports, and (5) opportunities for counter-seasonal supply. This paper focuses on the first two: structural changes in U.S. agricultural labor markets and rising labor costs, which directly affect states' comparative advantage relative to low-cost producers abroad.

2.2 Interstate Trade and Domestic Adjustment

Interstate trade is central to the U.S. food system as production is geographically concentrated while consumption is nationwide. As early as Finner (1959), researchers noted that interstate trade volumes in farm commodities vastly exceeded exports abroad, supported by regional specialization and transport networks. Later studies confirm that within-country trade still dwarfs international trade, reflecting deep economic integration but also persistent frictions in substitutability (Hillberry and Hummels, 2008; Anderson and Yotov, 2010, 2016).

More recent work highlights interstate trade as both a buffer and a propagation channel for local shocks. For example, Dall'Erba et al. (2021) show that during the 2012 Midwest drought, Nebraska's interstate crop exports collapsed while its interstate imports surged, illustrating how domestic trade reallocates commodities to absorb shocks. More broadly, integration across state markets stabilizes disparities in productivity and labor supply (Atkin and Donaldson, 2015; Coşar et al., 2022).

Spatial equilibrium models further demonstrate that regional shocks spread through domestic trade networks, redistributing both goods and factors (Monte et al., 2018). Because agriculture operates in a competitive, industrialized framework, tightly connected states transmit shocks quickly, generating measurable spillovers in productivity and competitiveness. For Fruits and vegetables, this geographic adjustment mechanism is critical: production is concentrated in specific states, but perishable products must reach consumers nationwide. Interstate shipments, heavily dependent on long-distance trucking, are the backbone of domestic food distribution. Perishability and seasonality increase reliance on these flows, since international imports cannot always substitute for timely supply. Thus, internal shipments not only ensure year-round availability but also underpin resilience in national food chains. Figure 8 shows the heatmap of heatmap of domestic, interstate trade for 2012.

2.3 U.S. Agricultural Labor Market

U.S. agriculture depends heavily on foreign-born labor, primarily from rural Mexico. Around 70 percent of crop workers are foreign-born, and roughly half of these lack legal status (Martin, 2017b). The National Agricultural Worker Survey consistently shows that hired labor in fruits and vegetables is disproportionately foreign-born and undocumented.

In recent decades, the number of seasonal farm workers in the U.S. has declined sharply. Explanations include stricter U.S. border and interior immigration enforcement (Luo and Kostandini, 2022; Luo et al., 2023; Kostandini et al., 2014), stronger local demand and higher wages in U.S. non-farm sectors (Castillo and Charlton, 2023), rising education and incomes in Mexico and the resulting exits from agriculture (Charlton and Taylor, 2020, 2016), increased competition from Mexican farms for domestic labor (Zahniser et al., 2018), and the reduced spatial mobility of an aging migrant workforce (Fan et al., 2015; Arteaga and Shenoy, 2023). This long-term contraction in supply has sharpened labor shortages in U.S. fruit and vegetable production (Martin, 2017a; Charlton and Kostandini, 2021; Rutledge and Mérel, 2023).

Simulations suggest that removing large numbers of undocumented workers would reduce U.S. agricultural production and exports. For California, removing half of undocumented farm workers would raise wages by 22 percent (Richards, 2018). At the national level, eliminating 5.8 million undocumented workers over 15 years would cut labor-intensive output by 2–4 percent and agricultural exports by 0.8–6.3 percent (Zahniser et al., 2012). Broader studies and industry reports suggest that such reductions would reverberate through the supply chain, cutting output and jobs beyond the farm sector (Farm Credit East, 2017).

2.4 Immigration Enforcement Policies

Modern interior enforcement took shape after the Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) of 1996, which laid out key authorities that later became templates for local–federal cooperation and employment verification. Following the 9/11 attacks, interior enforcement spending and activity increased sharply, and states and localities began adopting programs at different times and intensities. For empirical purposes, it is useful to distinguish two broad families of policies: police-based measures and employment-based measures.

Police-based measures involve collaboration between state or local law enforcement and federal authorities to identify, detain, and initiate the removal of noncitizens. Employment-based measures require or encourage employers to verify new hires' work authorization electronically. These programs rolled out on different timelines and at different jurisdictional levels, generating rich cross-place and over-time variation that I exploit in my analysis. I explain below the five policies I consider, which are further summarized in Table A1.

287(g) agreements (police-based, local). Beginning in the early 2000s, the Department of Homeland Security (DHS) entered into memoranda of agreement with county sheriffs' offices, municipal police departments, and state corrections agencies under Section 287(g) of the Immigration and Nationality Act. Participating officers received DHS training and were authorized, under federal supervision, to perform specified immigration functions. Agreements took several forms. Under "task-force" models, trained officers could question individuals encountered in the field, make arrests without a federal warrant under defined circumstances, and initiate removal processing. Under "jail-enforcement" models, screening focused on individuals already booked into local jails, with immigration status checks and detainers initiated from custody. Many jurisdictions adopted hybrid arrangements that combined field and jail components. Take-up expanded rapidly in the late 2000s: budgets increased, and over a thousand state and local officers were trained during this period. Adoption occurred at the county or state level, creating fine-grained spatial variation (Figures 10 and 13).

Secure Communities (police-based, local–national linkage). Launched in 2008 and rolled out nationwide by 2013, Secure Communities institutionalized biometric data sharing between local booking facilities and federal databases. When local law enforcement fingerprinted an arrestee, the prints were automatically checked against FBI and DHS systems;

potential immigration matches triggered notification to ICE, which could issue a detainer or initiate removal. The program emphasized individuals with criminal histories or prior immigration violations and effectively standardized status checks from booking onward. Secure Communities superseded much of the field-based screening under 287(g) and created near-universal coverage across counties during its initial period. It was later replaced by the Priority Enforcement Program (PEP) in 2015, which retained fingerprint-based screening but narrowed formal priorities; subsequent administrations later reinstated elements of Secure Communities. Figure 12 shows the spatiotemporal variation in SC implementation.

Omnibus immigration laws (police-based, state). Beginning around 2010, several states enacted comprehensive enforcement statutes that bundled multiple provisions, often including: (i) requirements or authorizations for officers to ascertain immigration status during lawful stops when warranted; (ii) limits on access to certain state-administered public benefits or licenses; (iii) provisions affecting cooperation with federal detainers; and (iv) penalties related to employment or harboring. While the specific mix varied by state, these laws tightened enforcement statewide and, importantly for identification, shifted policy at the state rather than county level. Arizona's SB 1070 is the best-known early example; related laws in other states created additional staggered adoption. Figure 11 illustrates the spatiotemporal variation in the adoption of the bill.

E-Verify mandates (employment-based, state). E-Verify is an electronic system operated by DHS in partnership with the Social Security Administration that allows employers to check a new hire's work authorization by submitting basic biographic information. Although federal contractors and agencies are required to use it, broader mandates arose through state laws that extended coverage to public agencies and their contractors, and in some cases to all private employers. The first statewide mandates appeared in the mid-2000s, and participation expanded rapidly thereafter. When an employer submits a query, the system returns either employment authorized or a tentative non-confirmation, which the worker can contest within a short time window. While E-Verify increases verification, it is not a perfect screen against identity fraud and has historically generated both false negatives and false positives due to data or input errors; nevertheless, state mandates measurably raise verification intensity at the point of hire. Figure 14 illustrates the spatiotemporal variation in E-Verify adoption.

2.5 Related Literature on Immigration Enforcement

A large literature examines how interior enforcement affects immigrants and local communities. Studies document impacts on undocumented populations (Bohn et al., 2014; Orrenius and Zavodny, 2016), labor markets (East et al., 2023; East and Velásquez, 2022), and education (Amuedo-Dorantes and Lopez, 2017a). Other work highlights consequences for children and families, including child welfare (Amuedo-Dorantes et al., 2015, 2018; Amuedo-Dorantes and Arenas-Arroyo, 2019; Amuedo-Dorantes et al., 2022), fertility (Amuedo-Dorantes et al., 2020), and mental health (Luo and Kostandini, 2023). Additional studies explore effects on self-employment (Amuedo-Dorantes et al., 2022) and political participation (Amuedo-Dorantes and Lopez, 2017b).

Agriculture-specific studies show that enforcement reduces farm labor supply (Ifft and Jodlowski, 2022; Luo and Kostandini, 2022; Luo et al., 2023), influences crop choices and profitability (Kostandini et al., 2014; Cruz et al., 2022), accelerates mechanization (Charlton and Kostandini, 2021), and lowers production (Rutledge and Mérel, 2023). Wage effects are often muted because farms substitute away from labor-intensive crops (Luo and Kostandini, 2022).

Trade-related work remains sparse. Devadoss and Luckstead (2011) and Zahniser et al. (2012) simulate impacts of immigration policy on agricultural exports using CGE and bilateral trade models. However, no reduced-form empirical studies examine how enforcement-driven labor supply shocks affect trade flows across states or internationally. This paper is the first to provide such evidence, linking interior enforcement to both interstate and international trade in labor-intensive crops.

3 Model

This section presents a gravity model, building on the canonical framework of Anderson and Van Wincoop (2003), in which I introduce an immigration enforcement term that shifts comparative advantage by raising variable production costs, tightening an effective labor constraint at harvest, and thereby reducing marketed sales. Goods are differentiated by origin (Armington) and preferences are CES, with multilateral resistance terms defined in general equilibrium and absorbed by fixed effects in the empirical implementation. To keep the model concise, I focus on one sector (fruits and vegetables) and allow origins to differ in a baseline labor-intensity index $\ell_i \in [0, 1]$ that scales the sensitivity of production technology and harvest outcomes to enforcement.

3.1 Preferences and Demand

Final demand in destination j is over origin varieties i with homothetic CES preferences and elasticity of substitution $\sigma > 1$. Let c_{ij} be consumption in j of the variety from i, $\alpha_i > 0$ be taste weights, and y_j be total expenditure. Utility is

$$U_j = \left(\sum_i \alpha_i^{\frac{1}{1-\sigma}} \, c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

Maximizing (1) subject to the budget constraint delivers the CES price index and bilateral expenditure shares:

$$P_j = \left(\sum_i \alpha_i \, p_{ij}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \qquad x_{ij} = \alpha_i \left(\frac{p_{ij}}{P_j} \right)^{1-\sigma} y_j, \tag{2}$$

where p_{ij} is the buyer price in j for the variety from i.

3.2 Technology, Enforcement, and Marketed Output

Let $\mu_i \geq 0$ denote immigration enforcement intensity at origin i. Let $\ell_i \in [0, 1]$ be an origin-specific labor-intensity index that can be measured from baseline crop composition or harvest labor shares. Enforcement shifts costs and quantities proportionally in logs with magnitudes scaled by ℓ_i.

Prices move proportionally with unit costs under constant markups, so I model the supply price as

$$P_i(\mu_i) = P_i^0 \exp\{\gamma\, \ell_i\, \mu_i\}, \tag{3}$$

where $\gamma \geq 0$ is a common semi-elasticity and P_i^0 is the baseline price. Biological (pre-harvest) quantity responds as

$$\tilde{Q}_i(\mu_i) = \tilde{Q}_i^0 \exp\{-\delta\, \ell_i\, \mu_i\}, \tag{4}$$

with $\delta \geq 0$. A harvest bottleneck reduces the share that reaches market according to

$$\theta_i(\mu_i) = \exp\{-\rho\, \ell_i\, \mu_i\}, \tag{5}$$

with $\rho \geq 0$. The marketed quantity is $Q_i^M(\mu_i) = \theta_i(\mu_i)\tilde{Q}_i(\mu_i)$. Combining (3)–(5), nominal marketed income that enters gravity is

$$\begin{aligned} Y_i(\mu_i) &= P_i(\mu_i)\, Q_i^M(\mu_i) \\ &= P_i^0 \tilde{Q}_i^0 \exp\{(\gamma - \delta - \rho)\, \ell_i\, \mu_i\} \\ &= Y_i^0 \exp\{(\gamma - \delta - \rho)\, \ell_i\, \mu_i\}, \end{aligned} \tag{6}$$

If $\ell_i = 0$, enforcement has no supply-side effect at origin i; if $\ell_i = 1$, enforcement applies with full strength.

3.3 Trade Costs and Delivered Prices

Let iceberg trade costs be $\tau_{ij} \geq 1$, meaning τ_{ij} units must be shipped for one unit to arrive. To capture substitution toward lower-enforcement origins, I allow a simple relative-enforcement tilt. For *domestic* pairs (i, j) with enforcement observed at both ends,

$$\tau_{ij} = \tau_{ij}^0 \exp\{\eta(\mu_i - \mu_j)\}, \qquad \eta > 0, \tag{7}$$

and the delivered price is

$$p_{ij} = P_i(\mu_i)\, \tau_{ij}. \tag{8}$$

For international destinations j without a comparable enforcement measure, I set $\tau_{ij} = \tau_{ij}^0 \exp\{\eta\, \mu_i\}$ and absorb destination-side conditions with foreign-region–year fixed effects in the empirical implementation.

3.4 Gravity with Multilateral Resistance

Market clearing implies $\sum_j x_{ij} = Y_i(\mu_i)$. Combining (2) with $p_{ij} = P_i(\mu_i)\tau_{ij}$ from (8) and imposing market clearing yields the multilateral resistance formulation:

$$x_{ij} = \frac{Y_i(\mu_i)\, y_j}{Y_W} \left(\frac{\tau_{ij}}{\Pi_i(\boldsymbol{\mu})\, P_j(\boldsymbol{\mu})} \right)^{1-\sigma}, \tag{9}$$

where Y_W is world nominal income in the sector, $\Pi_i(\boldsymbol{\mu})$ is outward multilateral resistance (origin-side), and $P_j(\boldsymbol{\mu})$ is inward multilateral resistance (destination-side).[1] Substituting (6) and (7) into (9) gives

$$x_{ij} = \frac{Y_i^0 \exp\{(\gamma - \delta - \rho)\, \ell_i\, \mu_i\}\, y_j}{Y_W} \left(\frac{\tau_{ij}^0 \exp\{\eta(\mu_i - \mu_j)\}}{\Pi_i(\boldsymbol{\mu})\, P_j(\boldsymbol{\mu})} \right)^{1-\sigma}. \tag{10}$$

[1] World income is $Y_W = \sum_j y_j$, the sum of all expenditures in the sector. Outward multilateral resistance $\Pi_i(\boldsymbol{\mu})$ measures how difficult it is for origin i to sell across all destinations given the vector of enforcement intensities, while inward multilateral resistance $P_j(\boldsymbol{\mu})$ measures how difficult it is for destination j to source goods from all origins. See Anderson and Van Wincoop (2003) for formal definitions.

3.5 Comparative Statics

Starting from the gravity expression in (10), taking logs gives

$$\begin{aligned}\log x_{ij} = \log Y_i^0 + (\gamma - \delta - \rho)\,\ell_i\,\mu_i + \log y_j - \log Y_W \\ + (1-\sigma)\Big[\log \tau_{ij}^0 + \eta(\mu_i - \mu_j) - \log \Pi_i(\boldsymbol{\mu}) - \log P_j(\boldsymbol{\mu})\Big].\end{aligned} \tag{11}$$

Own enforcement (μ_i). Differentiating (11) with respect to μ_i while holding other states' enforcement fixed yields

$$\frac{\partial \log x_{ij}}{\partial \mu_i} = (\gamma - \delta - \rho)\,\ell_i + (1-\sigma)\eta - (1-\sigma)\frac{\partial \log \Pi_i}{\partial \mu_i} - (1-\sigma)\frac{\partial \log P_j}{\partial \mu_i}. \tag{12}$$

The first term, $(\gamma - \delta - \rho)\ell_i$, is negative under the assumption that enforcement raises costs and reduces marketed output, with magnitude increasing in labor intensity ℓ_i. The second term, $(1-\sigma)\eta$, is also negative since $\sigma > 1$. Therefore, these imply that higher μ_i reduces exports, particularly for labor-intensive origins. Multilateral resistance adjustments enter through the last two terms, but are absorbed by fixed effects in the empirical implementation.

Partner enforcement (μ_j). Differentiating with respect to the partner's enforcement gives

$$\frac{\partial \log x_{ij}}{\partial \mu_j} = -(1-\sigma)\eta - (1-\sigma)\frac{\partial \log \Pi_i}{\partial \mu_j} - (1-\sigma)\frac{\partial \log P_j}{\partial \mu_j}. \tag{13}$$

Here the tilt term is $-(1-\sigma)\eta = (\sigma-1)\eta > 0$, so ignoring multilateral resistance adjustments, higher μ_j increases x_{ij}. Intuitively, when destination j enforces more strictly, its domestic costs rise and it shifts demand toward external suppliers such as i.

Enforcement in other partner states $k \neq j$ does not appear directly in (12)–(13), but their effects are embedded in the multilateral resistance terms $\Pi_i(\boldsymbol{\mu})$ and $P_j(\boldsymbol{\mu})$, and are therefore accounted for in the theoretical structure even if not shown explicitly. In practice, if alternative destinations for i (such as nearby states k) tighten enforcement, j becomes relatively more attractive as an outlet for i's exports, so some of i's shipments are diverted toward j.

Labor intensity (ℓ_i). The cross derivative with respect to labor intensity is

$$\frac{\partial \log x_{ij}}{\partial \ell_i} = (\gamma - \delta - \rho)\,\mu_i. \tag{14}$$

Since $(\gamma - \delta - \rho) < 0$, higher labor intensity amplifies the export contraction from own enforcement. This provides the heterogeneity prediction that crops or states with greater reliance on harvest labor are hit harder by immigration enforcement.

By symmetry, define $m_{ij} \equiv x_{ji}$. Holding multilateral resistance fixed, higher destination enforcement μ_i raises imports from any given partner through the enforcement differential in bilateral trade costs, with elasticity approximately $(\sigma - 1)\eta$. Higher partner enforcement μ_j lowers m_{ij} via the partner's supply term $(\gamma - \delta - \rho)\ell_j < 0$ and the same differential in trade costs. For foreign origins where μ_j is not observed, set $\mu_j \equiv 0$ and absorb origin conditions with origin region by year fixed effects in estimation. Aggregating over partners gives $\partial \log M_i / \partial \mu_i \approx (\sigma - 1)\eta$, so destination enforcement increases total imports.

In sum, the model embeds immigration enforcement in a CES Armington gravity framework where origin enforcement raises unit costs and reduces marketed quantities in proportion to labor intensity, and relative enforcement across partners shifts bilateral trade costs. These channels imply that higher origin enforcement contracts export most in labor-intensive places, while higher destination enforcement increases imports, with multilateral resistance absorbed by fixed effects in estimation. We next estimate these relationships empirically.

4 Data and Empirical Methods

4.1 Measuring Immigration Enforcement Intensity

I assemble data on the implementation of immigration enforcement policies from several sources: the year of SC implementation at the county level from East et al. (2023); E-Verify and the Omnibus Immigration Bill implementation at the state level from Luo and Kostandini (2023) and Orrenius and Zavodny (2015); and the 287(g) program implementation at the county and state levels from Kostandini et al. (2014).[2] I limit the sample to years prior to 2012 due to changes in the scope for Immigration and Nationality Act Section 287(g).[3]

I create the treatment variable denoting the state-level immigration enforcement intensity, ENF_{it}, using equation (15), which is similar to the approaches by Amuedo-Dorantes et al. (2018) and East et al. (2023). In the equation, $\mathbb{1}(E^k_{mc})$ is an indicator function that is equal to 1 if an immigration enforcement policy k, is active in county $c \in$ state i during month m[4] of year t. $A_{c,1997}$ and $A_{i,1997}$ are the population of agricultural workers for county c and state i, respectively, for 1997, the year prior to the rolling of the policies.[5] The data for the number of agricultural workers comes from the Quarterly Census of Employment and Wages (QCEW). $ENF^k_{it} \in [0,1]$ thus denotes the fraction of the state i where the policy k was active in year t, where counties are weighted by the number of agricultural workers population. I separately calculate the weighted share for five immigration policies: the E-Verify, the Immigration and National Act 287g agreements at the state and county levels,

[2]Whenever possible, I double-check the data using official sources from ICE and DHS.

[3]In 2012, the 287g agreements were greatly restructured due to the implementation of SC policy in nearly all counties of the U.S. Similarly, in 2014, the SC program was further replaced by the Priority Enforcement Program (PEP) that concentrated on individuals convicted of serious crimes or those who were deemed to pose a threat to public safety.

[4]I consider a month as treated if a county implemented the policy on or before the 15th of the month.

[5]Various economic papers use the baseline year population as the county weight. These papers usually look at the effects of immigration enforcement on variables like employment, wages, and other socioeconomic and demographic outcomes. Nonetheless, for this study, to analyze the impact on interstate agricultural trade, weighing counties by baseline population would not correctly grasp the intensity of effects on the agricultural sector as agricultural counties are more often than not rural and with lower populations. Therefore, I use the total agricultural worker population. I also conduct an analysis using the 1997 agricultural acres as the county weights as a robustness check. The state-year index values created using these two weights are highly correlated with each other.

the Secure Communities program, and the Omnibus Bill:

$$ENF_{it}^{k} = \frac{1}{A_{i,1997}} \sum_{c \in i} \frac{1}{12} \sum_{m=1}^{12} \mathbb{1}(E_{mc}^{k}) A_{c,1997} \tag{15}$$

I then create an index using these five weighted shares. Following the approach of Amuedo-Dorantes et al. (2018), I create the aggregate index by summing up the weighted shares of the policies as calculated from equation (15).[6]

$$ENF_{it} = \sum_{k \in K} ENF_{it}^{k} \tag{16}$$

Figure 9 shows the average enforcement intensity for 48 contiguous U.S. states from 2001-14 using this index. Figure 3 shows the spatiotemporal variation in the immigration enforcement intensity over time.[7] For a better interpretation of coefficients, I also use the normalized version of this index.[8]

4.2 Effects on Farm Labor Expenses and Crop Production

The analysis of the trade effects of immigration enforcement policy is based on the premise that immigration enforcement reduces the availability of farm workers in the implementing

[6]The index assigns equal weights to the five disparate policies, where equal weights assume that all policies contribute equally to the enforcement, which may not be true. The policies differ significantly in their nature, with some focusing on stopping public services to undocumented immigrants, others on stopping and verifying the legality of immigrants, and others disincentivizing employers from hiring undocumented immigrants. Given these differences, determining appropriate weights for their effects on the presence of undocumented immigrants is not feasible. The effects on their presence in a jurisdiction could result from direct deportations, out-migration to other U.S. states, or a decrease in in-migration from Mexico or other U.S. states. Therefore, considering these factors, I use equal weights for the policies.

[7]Most of the variation in immigration enforcement intensity occurs between 2007 and 2012. In earlier years (1997 and 2002), nearly all states had zero values. However, because the enforcement measure is continuous at the state-by-year level, the analysis exploits variation in the intensity of enforcement across states and years rather than relying on binary treatment timing.

[8]While many papers have employed this method, most existing work examining immigration enforcement has focused narrowly on the effects of a single policy at a time. The aggregate consequences of simultaneous policies can differ markedly from those of individual measures. Interacting policies may generate complementarities or nonlinearities, producing combined effects that are larger or qualitatively different than the sum of their parts. Understanding these joint effects is crucial not only for evaluating immigration enforcement as a whole but also for advancing broader debates on how overlapping policy interventions shape labor markets, production, and trade.

jurisdiction, and, consequently, this reduction decreases the production of labor-intensive commodities such as fruits and vegetables, which may affect their consumption and trade. More broadly, immigration enforcement can be seen as a labor market distortion that alters the relative supply of inputs across states. By constraining labor availability, these policies shift the production possibility frontier for agriculture, potentially inducing substitution toward mechanization, crop reallocation, or higher reliance on imports. The resulting adjustments go beyond local production outcomes and have implications for regional specialization, trade flows, and welfare. Therefore, before discussing the trade effects of enforcement, it is essential to establish the relationship between immigration policy, farm worker availability, and the production of fruits and vegetables.

Although a few previous studies have shown that immigration enforcement negatively impacts these variables (Kostandini et al., 2014; Luo and Kostandini, 2022), they primarily focus on the effects of a singular policy at a time. I use the aggregated immigration enforcement indices created in section 4.1 to analyze these effects. I employ the data from the Census of Agriculture (CoA) by the USDA National Agricultural Statistics Service (NASS). The CoA is a nationwide survey on detailed agricultural variables conducted by USDA NASS every five years in years ending in digits 2 and 7. I use the data from 1997, 2002, 2007, and 2012. I apply the fixed effects regression specification shown in equation (17).

$$y_{it} = \Omega_i + \Lambda_t + \alpha ENF_{it} + X'_{it}\beta + \varepsilon_{it} \tag{17}$$

In equation (17), y_{it} is the outcome variable in the state, i, and year, t. I look at the effects on four outcomes: total labor expenses (hired and contract) as a percentage of the total operating costs, total agricultural labor expenses (hired and contract), and total sales of fruits, nuts, and vegetables. The terms Ω_i and Λ_t denote the state and year fixed effects, respectively to control for unobserved heterogeneity that may vary across states but are constant over time, and unobserved heterogeneity that may vary over time but are constant across states.

X_{it} is a vector of time-variant state-level covariates, including a control for local labor demand shocks and weather variables. The sources and creation of these variables are explained in Section 4.4. Finally, ε_{it} is the idiosyncratic standard errors clustered at the state level.

4.3 Effects on Trade

4.3.1 Data Source

For the trade analysis, I use the Freight Analysis Framework version 5 (FAF-5) created by the Oak Ridge National Laboratory with the support of the Bureau of Transportation Statistics and the Federal Highway Administration. FAF-5 relies on various sources, such as the agricultural census and the merchandise trade statistics, and produces origin-destination figures (both in monetary value and actual weights) across the U.S. states, metropolitan areas, and foreign continents. Disaggregation by commodity in the FAF-5 uses a two-digit sectoral classification of transported goods (SCTG). I use the SCTG product code of "03" which includes fruits, vegetables, horticulture, and seeds,[9] which are often the most impacted crop types due to local, seasonal labor shortages. I also use the SCTG product codes for cereal grain crops, animal feed, and milled grain products, and other prepared food products, for falsification tests, as they are highly capital-intensive and less labor-intensive, and thus, immigration policy should not affect the production and trade of cereal crops as much.

The FAF-5 data is available from 1997 in five-year intervals for years ending in "2" and "7". I use the data from 1997, 2002, 2007, and 2012. For the domestic trade flows, FAF-5 measures the trade flow between each state. For international trade, it measures trade between each U.S. state and continent except for Canada and Mexico, for which there is

[9]The SCTG code "03" includes fruit and nuts (edible, fresh, chilled, or dried), vegetables (edible, fresh, chilled, or dried), fruits and juices, nuts, tobacco (not steamed or stripped), live plants or parts of plants, and oil seeds. More information: https://www.bts.gov/sites/bts.dot.gov/files/docs/browse-statistical-products-and-data/surveys/commodity-flow-survey/210866/2017-cfs-commodity-code-sctg-manual.pdf

data at the state-country level.

FAF-5 is uniquely suited for this analysis because it provides consistent measures of both interstate and international trade flows within a single framework. Unlike most trade datasets that capture only international shipments between countries or domestic shipments within countries, FAF-5 integrates both in a comparable format. It extends the Commodity Flow Survey (CFS), which is limited to sampled establishments, by incorporating customs records, the agricultural census, and other administrative sources to create a comprehensive origin–destination–commodity–mode database. Each shipment is identified by its origin (domestic or foreign), destination (domestic or foreign), commodity classification at the 2-digit SCTG level, and mode of transportation, with flows reported in both monetary value and physical tonnage.[10] A further strength of FAF-5 is its geographic resolution: flows are available for states, 132 domestic FAF regions (metropolitan areas and state remainders), and 8 foreign regions, enabling precise analysis of how goods move across U.S. states and international borders in relation to state-level enforcement policies.

The FAF-5 dataset has several limitations. First, its five year periodicity constrains temporal coverage, although this timing aligns with the Census of Agriculture and the construction of my enforcement index, allowing consistent integration across sources. Second, commodity codes are reported in aggregated categories, for example fruits and nuts are grouped with seeds, but these remain among the most labor-intensive commodities and therefore the most relevant for testing enforcement effects. In addition, while aggregation across highly dissimilar sectors can introduce bias in gravity models (Redding and Weinstein, 2019), this concern is limited here because fruits and vegetables are relatively homogeneous in trade relevant characteristics.[11]

[10] In this analysis, I focus on monetary values, which provide a consistent measure of economic activity across commodities and states.

[11] Unlike aggregations across sectors such as manufacturing and natural gas, which differ widely in trade elasticities and responses to policy shocks, fruits and vegetables share similar production processes, perishability, labor intensity, and sensitivity to trade costs. Although some heterogeneity may exist within this category, it is unlikely to introduce meaningful aggregation bias in estimating the effects of immigration enforcement on total fruit and vegetable trade flows.

Third, international flows are reported for broad foreign regions rather than individual countries, which limits the ability to distinguish bilateral patterns of trade and may attenuate heterogeneous effects across individual trading partners.[12] Finally, although FAF-5 aims to allocate shipments to their ultimate origins and destinations, some flows may still appear concentrated in port states that serve as initial entry or exit points. For imports, the recorded flows may reflect logistical entry rather than final destination, and for exports, shipments may be attributed to port states even when production originates elsewhere. I return to this issue in Section 5.3.1, where I address the exit and entry point effects by distinguishing logistical port activity from local demand.

4.3.2 Empirical Framework

To analyze the effects of intensified immigration policy on labor-intensive agricultural commodity trade, I estimate the Poisson Pseudo-Maximum Likelihood (PPML) estimator illustrated in equation (18), which is loosely derived from the structural gravity model by Anderson and Van Wincoop (2003) and closely follows Tong et al. (2019). PPML addresses heteroskedasticity biases of log-linear gravity models and accommodates zero trade flows (Silva and Tenreyro, 2006; Shepherd et al., 2013).[13]

$$EX_t^{i \to j} = \exp\Big[\alpha ENF_{it} + \Gamma_{jt} + \Psi_{ij} + X'_{it}\beta + \lambda_i t\Big] \times \varepsilon_{ijt} \tag{18}$$

In the equation, i, j, and t index exporter, importer, and year respectively. $EX_t^{i \to j}$ is the volume of labor-intensive agricultural commodities exported from U.S. state i to state,

[12] FAF-5 aggregates foreign origins and destinations into eight regions: Canada, Mexico, Rest of the Americas, Europe, Africa, Southwest and Central Asia, Eastern Asia, and Southeast Asia and Oceania.

[13] Unlike difference-in-differences or event study designs, my empirical strategy does not rely on a parallel trends assumption. The specification is a gravity framework with importer-year and dyadic fixed effects, where the key regressor is a continuous measure of state-level immigration enforcement intensity. Identification comes from within-exporter-importer-pair variation in enforcement intensity over time, conditional on fixed effects and covariates. The assumption required is strict exogeneity of the enforcement index with respect to contemporaneous shocks to trade flows, not parallel pre-trends between treated and untreated states.

country, or region j in year t.[14] The primary explanatory variable is ENF_{it}, which measures immigration enforcement intensity in exporter state i in year t. I describe the creation of this variable in Section 4.1. The term Γ_{jt} denotes importer-year-specific effects, which account for all importer-specific trade-promoting and trade-restricting components that determine the extent of multinational resistance from the importer's side (Yotov et al., 2016).[15] Several other factors like the importer's GDP (Anderson and Van Wincoop, 2003) and currency exchange rate volatility (for international trade) (Bacchetta and Van Wincoop, 2000; Auboin and Ruta, 2013) also determine the trade volume. Destination-by-year fixed effects, Γ_{jt}, also control for these bilateral trade costs and factors determining the importer's ease of market access.

The importer-year fixed effects treat trade policies of a particular importer region, j, as constant for all of its export partners and may not capture the exporter-specific time-variant trade policy. However, since all of the exporter states in this study are U.S. states, and assuming that the importer-level policies do not vary between U.S. states,[16] that should not bias the estimates.[17] One particular limitation of the importer-year fixed effects, however, is that they average across all goods that the importer trades with U.S. states without addressing the fact that states specialize in the production of different goods that might be subject to different trade policies. The fact that I limit the sample to fruits, vegetables, and seeds alleviates this issue if there are no differential policies placed for different fruit and vegetable types.

The term Ψ_{ij} denotes the dyadic importer-exporter pair fixed effects, which control for time-invariant pair characteristics like whether they share a border and the distance between each other. The term also encompasses state fixed effects (origin fixed effects and destination

[14] For the entire analysis, I use both the monetary value (in 2023 million U.S. dollars) and the weight (in thousand tons) of export and import.

[15] Such as the trade agreements, subsidies, quotas, tariffs, preferential trade policies, and embargoes, just to name a few.

[16] For example, if a country adds tariffs to U.S. products, they do not differentially impose tariffs on one U.S. state vs. another; the tariff is constant throughout all U.S. states, which is a reasonable assumption.

[17] This approach could be problematic, though, in case of a country-level analysis instead of a U.S.-state-by-country level analysis with differential importer-level policies for different exporting countries.

fixed effects separately). The inclusion of Γ_{jt} and Ψ_{ij} collectively also accounts for state-level factors that are more likely constant over time at the state level but which may have experienced slight changes over the sample years, including the transportation costs (Geraci and Prewo, 1977; Hummels, 2007) and relative factor price differentials (Hilton, 1984).

To predict the total trade volume between two partners, the gravity model by Anderson and Van Wincoop (2003) includes importer-year fixed effects and exporter-year fixed effects to control for importer-specific and exporter-specific time-variant shocks, respectively. However, because the primary explanatory variable is exporter immigration policy intensity, which is time-variant, including exporter-year fixed effects would absorb this variation. Therefore, I do not include exporter-year fixed effects in the model. Instead, I control for several exporter-specific time-varying variables affecting agricultural production and trade, denoted in the equation as vector X_{it}. Similar to the fixed effects regression to analyze production effects as laid out in equation (17), I use the shift-share labor demand shock control, weighted state-level temperature and precipitation measures, and the weighted average of enforcement intensities in trade partners states as control variables. These variables are explained in Section 4.4.

Furthermore, we include state-specific linear time trends, denoted by $\lambda_i t$, to capture unobserved factors that evolve gradually within states, such as long-run changes in crop composition, infrastructure, or demographics. This specification helps ensure that estimated enforcement effects are not conflated with these underlying trends, thereby strengthening identification.

The term ε_{ijt} is the idiosyncratic standard error clustered at the origin-by-destination level. The primary coefficient of interest, α_1, exploits the within-exporter-importer-pair variation in immigration enforcement intensity over time. The identifying assumption of my empirical strategy is that the time-varying shocks, ε_{ijt}, are orthogonal to the treatment variable. In Section 4.5, I discuss the plausible exogeneity of the enforcement intensity variable, and in Section 6.3, I further address and refute any endogeneity concerns related to the treatment variable.[18]

4.3.3 Extensions for Import Analysis

To analyze the effects of immigration enforcement intensity on imports, I estimate equation (19), which is identical to equation (18) that I use for the export analysis, except for a few adjustments. The outcome variable is $M_t^{j \leftarrow i}$, which denotes the total imports from i to states j in year t. I replace origin-level enforcement index and covariates with destination-level enforcement index, ENF_{jt}, and covariates, and switch the destination-by-year fixed effects with origin-by-year fixed effects, Γ_{it}, to control for time-varying exporter-specific trade-promoting and trade-restricting components, as well as the bilateral trade costs and factors determining the exporter's easy of market access.

$$M_t^{j \leftarrow i} = exp\Big[\alpha ENF_{jt} + \Gamma_{it} + \Psi_{ij} + X'_{jt}\beta + \lambda_j t\Big] \times \varepsilon_{ijt} \tag{19}$$

This specification estimates the effects of the destination-specific enforcement intensity on trade, controlling for destination-specific variables that may affect their agricultural production and exporter-specific trade-regulating components.

4.4 Covariates

The regressions described above include a set of time-varying covariates under vector X_{it} to absorb alternative channels through which local economic and climatic conditions may affect agricultural production and trade.

[18] I do not use any regression weights. Even without explicit analytic weights, the PPML estimator implicitly gives greater influence to larger trade flows, since the likelihood contribution of each observation scales with the magnitude of the dependent variable. In practice, this means that observations with higher export or import volumes carry more weight in shaping the coefficients compared to smaller flows.

4.4.1 Labor Demand Shocks

I include the shift-share measure of labor demand as a control (Bartik, 1992; Goldsmith-Pinkham et al., 2020), which is given by

$$\sum_k (s_{ik0} \times g_{kt}) \tag{20}$$

where s_{ik0} is the share of employment in industry k in the baseline year, 1997, and g_{kt} is the national growth rate of industry k in year t with respect to the baseline year. The growth variable, g_{kt}, is equal to $\frac{Emp_{kt}}{Emp_{k0}}$ where Emp_{kt} and Emp_{k0} denote the total employment in industry k in year t and the total employment in industry k in the baseline year, 1997, respectively. I construct this variable using the Quarterly Census of Employment and Wages (QCEW) from the U.S. Bureau of Labor Statistics (BLS). Adding this term to the regressions accounts for the changes in economic conditions that might affect the volume of labor-intensive agricultural commodity production or trade. As the sample period spans the Great Recession, the shift-share control helps to isolate the effects of the local economic shocks arising from the recession. As the shift-share variable is constructed using national industry trends and the state's initial industry structure, it acts as an exogenous source of variation in local labor demand.[19]

4.4.2 Weather

Weather controls include agricultural-acreage-weighted state-level precipitation and temperature, using the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) data from the PRISM Climate Group at Oregon State University.[20] Regarded as one of the most reliable interpolation procedures for climatic data on a small scale, the model is used by NASA, the Weather Channel, and various professional weather services (Deschênes and

[19]While traditionally, the shift-share variable is used as an instrument, several recent papers use it as a regression control variable (Beerli et al., 2021; East et al., 2023).

[20]PRISM data is available in the following link: https://prism.oregonstate.edu/

Greenstone, 2007). PRISM generates precipitation and temperature at 4 $\times$ 4 kilometer grid cells for the entire U.S. For precipitation, it considers the orographic effect, where mountains influence precipitation patterns, by modeling how air masses interact with terrain. For temperature, it uses observations from weather stations, considering factors such as elevation, aspect, and coastal proximity to model temperature distributions (Daly et al., 2008). I use the county-level annual precipitation and temperature and weigh the counties using 1997 county-level agricultural acreages extracted from the CoA to create state-level weighted means for the variables.

4.4.3 Trade Partner Enforcement

When analyzing the effects of immigration enforcement in a given U.S. state i on its exports to state j, a key concern is that enforcement policies in other U.S. states that also import from i may indirectly affect this bilateral trade flow. Specifically, if state i exports to multiple domestic destinations, and some of those partner states $k \neq i$ intensify immigration enforcement, the resulting labor shortages may lower their in-state production and increase their reliance on imports from state i. This shift in demand may inflate observed exports from i to j, even if enforcement in i itself had no direct effect. Failing to account for these spillover effects can bias estimates by overstating the role of i's enforcement in driving exports to j. Such spillover effects raise the possibility of violating the Stable Unit Treatment Value Assumption (SUTVA), which requires that the treatment in one unit not affect outcomes in another.

To address this concern, I construct a weighted immigration enforcement index for state i's domestic export partners, denoted ENF_{it}^{P}, which captures enforcement levels in other U.S. states that import from i. I use this as a control variable for my trade regressions. The weights ω_{ik} are based on the share of i's total domestic exports sent to each partner state

$k \neq i$ in a baseline year. Mathematically,

$$ENF_{it}^{P} = \sum_{k \neq i} \omega_{ik} \cdot ENF_{kt} \tag{21}$$

where ENF_{kt} is the enforcement intensity in state k at time t.

For the import specification, a similar concern arises if immigration enforcement in other U.S. states that also export to i shifts their production capacity and trade orientation. To address this, I construct an analogous weighted partner index for i's import origins, ensuring that enforcement-induced supply shocks in origin states are not conflated with the effects of i's own enforcement.

4.4.4 Soybean Production

Finally, as noted in Section 4.3.1, FAF-5 groups several crops into broad categories. For this analysis, I use product code "03," which covers fruits and vegetables but also includes soybeans, a major capital-intensive crop. To address this issue, I control for state-level soybean production in the regressions.[21] Although this aggregation could bias the estimated coefficients toward zero, as we discuss in Section 5, the results remain largely statistically and economically significant, albeit potentially with some downward bias. This concern is less relevant for the international import analysis, since the United States does not import soybeans in large quantities. Furthermore, as a robustness check, I also re-estimate the international export regressions both excluding and restricting the sample to the top soybean-producing states, given that soybeans are aggregated with fruits and vegetables in the FAF product code despite being far less labor-intensive.

[21] Figure 15 shows the total national soybean production and export of soybeans between 1990 and 2022.

4.5 On the Exogeneity of Immigration Enforcement to Trade

State-level immigration enforcement policies are largely shaped by political and institutional factors rather than by short-run movements in agricultural trade. The timing of initiatives such as E-Verify mandates, Omnibus Immigration Bills, or 287(g) agreements reflects legislative calendars, partisan control, or cooperation between local sheriffs and federal authorities, rather than contemporaneous export fluctuations. The scope of these policies is also broad. They target undocumented populations across a range of sectors, making it unlikely that their intensity was designed in response to the performance of labor-intensive crop trade specifically. This institutional separation between the drivers of enforcement and the dynamics of agricultural trade supports the view that enforcement intensity can be treated as predetermined with respect to trade flows.

The research literature supports this interpretation. Amuedo-Dorantes and Bansak (2012) find that state adoption of E-Verify systems was driven primarily by political considerations, not short-term labor market fluctuations. Watson and Riffe (2013) shows that local immigration enforcement reflects longer-term demographic and political climates rather than contemporaneous economic performance. Bohn and Pugatch (2015) demonstrate that variation in border enforcement is explained by federal budget cycles rather than local labor shocks. Similarly, East et al. (2023) exploit the staggered rollout of Secure Communities, which was dictated by federal implementation strategies, to show that enforcement reduced employment but was not timed to respond to local trade dynamics. These studies reinforce the view that, conditional on importer-year and dyadic fixed effects as well as the covariates described in Section 4.4, state-level immigration enforcement can be treated as plausibly exogenous to short-run movements in agricultural trade. Nonetheless, I conduct several tests to address endogeneity concerns in Section 6.3.

5 Results

5.1 Effects on Farm Labor Expenses and Crop Production

Before discussing the trade effects of immigration enforcement, it is imperative to establish the relationship between immigration policy, farm labor outcomes, and agricultural production that drives the trade dynamics. Table 1 shows the effects of immigration enforcement on farm labor expenses and production using equation (17) and state-level USDA NASS Census of Agriculture data from 1997, 2002, 2007, and 2012. I examine three outcome variables: (1) total labor expenses (hired and contract) as a percentage of total operating costs, (2) total agricultural labor expenses (hired and contract), and (3) total production of fruits, nuts, and vegetables.

Results in columns (1) and (2) of Panel B show that a one–standard-deviation increase in immigration enforcement intensity (equal to the average enforcement in 2012) leads to a 2.6 percent decrease in the labor-expense share of operating costs and a 7.6 percent decrease in total agricultural labor expenses, respectively. Coefficients from regressions using the non-normalized index are comparable to those using the normalized treatment, although slightly smaller in magnitude. Despite potential upward pressure on wages from tighter labor supply (Kostandini et al., 2014), these declines in labor spending are consistent with a reduction in the number of hired workers. Likewise, column (3) shows that a one–standard-deviation increase in enforcement intensity decreases fruits–nuts–and–vegetables sales by 6.9 percent, statistically significant at the 1 percent level.

Taken together, the decline in labor expenditures alongside a sizable contraction in FV output points to an enforcement-induced tightening of the effective harvest-labor constraint rather than pure wage pass-through. This mechanism is consistent with evidence that immigration enforcement lowers hired farm employment, accelerates substitution toward machinery, and shifts acreage away from labor-intensive crops (Luo and Kostandini, 2022, 2023; Charlton et al., 2023; Rutledge and Mérel, 2023; Cruz et al., 2022). In the context of perishable horticulture, smaller marketed volumes at origin naturally propagate downstream: buyers fill gaps by reallocating procurement toward lower-enforcement states and, when domestic reallocation is insufficient, by increasing foreign sourcing. The trade results that follow should therefore be interpreted as the aggregate manifestation of these farm-level adjustments.

5.2 Effects on Domestic Trade Flows

I start by discussing the effects on domestic trade flows. Table 2 shows the effects of immigration enforcement on the interstate export of fruits and vegetables. All regressions use the reduced-form gravity model with the PPML estimator illustrated in equation (18) and the FAF-5 dataset from 1997, 2002, 2007, and 2012. I present results using trade flows measured in monetary value (in million U.S. dollars, adjusted to 2012 values). Each regression is shown in three versions: starting with only fixed effects and no covariates, then adding state-level covariates, and finally including both state-level covariates and trading partners' enforcement intensity. Panels A and B show results for domestic (interstate) exports, while Panels C and D show results for domestic (interstate) imports. Panels A and C use the raw enforcement index as the regressor, while Panels B and D use its normalized version. For ease of interpretation, I focus the discussion on regressions using the normalized index.

Panel B, column (4) shows that a one standard deviation increase in enforcement intensity is associated with a 20.15 percent $((\exp(-0.225) - 1) \times 100)$ decrease in the outflow of fruits and vegetables to other U.S. states in terms of monetary value.

Panels C and D use equation (19) to analyze the effects of enforcement intensity on FV imports from other U.S. states. Column (4) shows the results from the preferred specification. Panel D, column (4), shows that a one standard deviation increase in enforcement intensity is associated with a 21.54 percent increase in FV trade inflows from other U.S. states in terms of monetary value, which is statistically significant at 1 percent level.

These results highlight the important role of immigration enforcement in shaping domestic, interstate trade patterns for labor-intensive agricultural commodities. This reallocation of trade within the U.S. reflects how policy-driven labor supply shocks can shift the spatial organization of agricultural production and the economic geography of distribution.

5.2.1 Accounting for Trade Partner's Enforcement Intensity

If immigration enforcement intensity decreases the outflow of fruits and vegetables to other U.S. states and increases their inflow, then which states supply the FVs flowing in? The primary fixed effects gravity model in equation 18 accounts for immigration enforcement intensity at the origin state but not at the destination state, which is absorbed by the destination-by-year fixed effects, Γ_{jt}, as well as the weighted average of the trade partners' enforcement levels. Holding the origin state's immigration enforcement intensity constant, the enforcement intensity at the destination may also affect the volume and direction of interstate trade. For instance, if a destination state experiences a decline in domestic FV production, it may increase trade demand to reduce local shortages.

To investigate whether trade flows vary depending on the enforcement intensity of the destination, I incorporate an interaction term between destination-state enforcement and a binary indicator for high-enforcement origin. This indicator equals 1 if the origin state's enforcement intensity exceeds the median, and 0 otherwise.[22,23] This approach allows me to assess whether origin-state enforcement moderates the effect of destination-state enforcement on trade.

Table A2 presents the results of this analysis. Panels A and B show results using the enforcement intensity and its normalized version, respectively, as the treatment variable. Column (4), which shows results from our preferred approach, shows that a one standard deviation increase in enforcement intensity leads to a 37.30 percent increase in imports from states with below-median enforcement, while the difference in imports from above-median

[22]As in the main analysis, I use both the normalized index and the summation index to define enforcement intensity, constructing the high-enforcement dummy based on each index's respective median.

[23]Specifically, I take the maximum enforcement intensity observed in each state over the four survey years and calculate the median value across states.

enforcement states is a 19.51 percent reduction.

This result shows the importance of considering the enforcement environment of both trade partners when analyzing domestic agricultural trade. Not only does destination-state enforcement matter for trade flows, but the enforcement intensity at the origin also shapes substitution patterns. States with lower enforcement may act as critical suppliers during periods of tightened enforcement elsewhere. This highlights a previously underappreciated mechanism through which immigration policy indirectly affects the reallocation of domestic trade in agriculture.

5.3 Effects on International Trade

Now we turn our focus to international trade. Unlike domestic interstate flows, which capture the reallocation of fruits and vegetables across U.S. states in response to labor supply shocks, international flows depend on how these shocks interact with broader patterns of comparative advantage, foreign supply capacity, and import infrastructure. In this context, immigration enforcement may influence not only the competitiveness of U.S. producers in foreign markets but also the extent to which domestic shortages are offset by imports from abroad. The international trade margin, therefore, provides a complementary perspective: whereas domestic trade reallocates production within the country, international trade outcomes reveal whether foreign partners step in to fill gaps created by enforcement-induced reductions in local labor supply.

Table 3 shows the results analyzing the effects of state-level immigration enforcement on international trade. Given the aggregation level of the FAF-5 dataset, in these regressions, the level of observation is U.S.-state-to-region unless the foreign trade partner is either Mexico or Canada, in which case the level of observation is U.S.-state-to-country. All regressions use the PPML estimator illustrated in equation (18) and the FAF-5 dataset from 1997, 2002, 2007, and 2012. Similar to previous tables, each regression is shown in three versions: starting with only fixed effects and no covariates, then adding state-level covariates, and finally including both state-level covariates and trading partners' enforcement intensity. Panels A and B show results for international exports, while Panels C and D show results for international imports. Panels A and C use the raw enforcement index as the regressor, while Panels B and D use its normalized version. For ease of interpretation, I focus the discussion on regressions using the normalized index.[24]

Panel B, column (4) shows that a one standard deviation increase in enforcement intensity is associated with a 11.13 percent decrease in the outflow of fruits and vegetables to foreign export partner countries in terms of monetary value. Although not statistically precise, the point estimates suggest a potentially negative relationship.

Panels C and D use equation (19) to analyze the effects of enforcement intensity on FV imports from foreign import partner countries. Column (4) shows results from the preferred specification for trade in terms of monetary value. We find that a one standard deviation increase in enforcement intensity is associated with a 12.86 percent increase in imports of fruits and vegetables. It is worth noting that column (3), which omits state-specific linear time trends, yields a PPML coefficient close to zero (–0.007), suggesting little to no measurable effect in that specification. This implies that unobserved state-specific trends may be driving the dynamics of FV imports; once these are properly accounted for, the underlying positive effect of enforcement intensity becomes evident.

FAF-5 dataset is at the level of U.S.-state-to-foreign-continents, unless it is either Mexico or Canada, two of the largest import partners for labor-intensive crops for the United States. Mexico and Canada are the largest import partners of the U.S., comprising 58.5 percent and

[24]To assess whether our international export results are driven by the inclusion of soybeans, a crop that is capital- rather than labor-intensive but aggregated into the same FAF category as fruits and vegetables, I conduct a set of robustness checks. In Table A4, Panels A-B, we re-estimate the regression excluding the top 10 soybean-producing states as origins. The coefficient on enforcement remains negative, though imprecisely estimated, consistent with the expectation that enforcement should reduce exports of labor-intensive crops rather than soybeans. In Table A4, Panels C-D, we restrict the sample to these soybean-heavy states and find null effects, with coefficients close to zero and statistically insignificant. Together, these patterns indicate that our main findings are not driven by soybean exporters and that the negative relationship between enforcement and exports is concentrated in crops with greater labor intensity. As stated earlier, the issue with soybean inclusion affects only the export analysis, not the international import analysis, as the United States does not import soybeans in large quantities.

8.9 percent of FV imports, respectively, in 2022. Therefore, alongside the effects on imports in aggregate, we also look at the effects on imports specifically from Mexico and Canada, which is shown in Table A3.

Panels A and B use equation (19) to analyze the effects of enforcement intensity on FV imports from Mexico. Column (4) presents results from the preferred specification, where trade is measured in monetary value. We find that a one–standard deviation increase in enforcement intensity is associated with a 25.73 percent increase in fruit and vegetable imports from Mexico. Consistent with the broader import analysis, omitting state-specific time trends reverses the direction of the estimated effects and alters both their magnitude and statistical significance.

Panels C and D report the effects on imports from Canada. Across specifications, we do not find any statistically significant effects of immigration enforcement at the U.S. state level on imports from Canada.

5.3.1 Exit and Entry Point Effects: Evidence from Port States

Although the FAF-5 data aim to allocate exports to their true origins, in practice some goods may still be recorded in port states that serve as the point of exit and redistribution. Similarly, imports may be recorded in port states that serve as the initial point of entry into the country. In both cases, the port itself may appear as the source or destination even though traded products are subsequently supplied from or to other U.S. states. If this channel is not taken into account, the estimates could conflate true production or consumption effects with logistical exit and entry effects.

To capture this heterogeneity, I interact the weighted enforcement intensity of a state's domestic trade partners with an indicator for being a major fruit and vegetable port state. To ensure that the results are not conflated with the fact that some of the largest port states are also the largest producers of fruits and vegetables, I exclude those states and focus on ports where local production is relatively limited. This approach allows me to test whether trade substitution in response to domestic enforcement shocks is disproportionately concentrated at critical exit (entry) points for fruit and vegetable exports (imports), where both direct consumption (production) demand and logistical concentration of flows may amplify the effects of enforcement.

Table A5 shows that the presence of major fruit and vegetable export ports does not significantly mediate the response of international trade to immigration enforcement. The direct enforcement effect on exports is negative but highly imprecise, consistent with earlier results showing no robust adjustment along the foreign export margin. Likewise, the interaction between enforcement in a state's domestic import partners and the indicator for being a prominent FV export port is positive (0.26) but statistically insignificant, suggesting that exit points do not meaningfully amplify substitution dynamics.

Table A6 shows that the presence of major fruit and vegetable port states strongly mediates the international trade response to immigration enforcement. The direct enforcement effect on exports is small and imprecisely estimated, consistent with earlier results showing limited adjustment along the foreign export margin. By contrast, the interaction between enforcement in a state's domestic export partners and the indicator for being a prominent FV port state is large, positive, and highly significant at 29.3 percent. This means that when enforcement intensifies in domestic supplier states, the substitution toward international imports is disproportionately concentrated in port states that serve as gateways for fruits and vegetables.

This result thus suggests that ports amplify immigration enforcement shocks by concentrating substitution toward international imports. It shows that import infrastructure, not just production, is central to how labor market policies shape trade outcomes.

6 Robustness Checks

6.1 Controlling for Worker Inflows

Immigration enforcement in other U.S. states may induce workers to relocate into a given state. Beyond direct relocation, enforcement can also create broader chilling effects that discourage workers, particularly those with uncertain status, from participating fully in labor markets or moving across state borders. As a result, labor supply in one state may be shaped not only by its own enforcement policies but also by the enforcement climate in other jurisdictions. Ignoring these spillovers risks conflating local enforcement effects with those driven by worker inflows or deterrence linked to neighboring states. To account for this possibility, we construct a weighted inflow index based on historical migration flows that captures the extent to which enforcement elsewhere is likely to affect labor availability in the state.

To account for this potential inflow channel, we construct a weighted inflow index using baseline migration flows from the 2001 American Community Survey (ACS), specifically the variable identifying the state of residence one year prior.[25] Let $M_{k\to i,0}$ denote the number of workers (across all industries) who resided in state k one year prior to 2001 and who reside in state i in 2001. We then define weights

$$w_{k\to i} \;=\; \frac{M_{k\to i,0}}{\sum_{\ell\neq i} M_{\ell\to i,0}}, \tag{22}$$

so that $\sum_{k\neq i} w_{k\to i} = 1$. These weights capture the share of state i's baseline worker inflow that originated from each state $k \neq i$.

Using these weights, we construct an inflow enforcement index for each state i and year t:

$$ENF_{it}^{IN} \;=\; \sum_{k\neq i} w_{k\to i}\, ENF_{kt}, \tag{23}$$

[25] For respondents who lived in a different residence 1 year before the survey date, the ACS identifies the state (or outlying territory or foreign country) where the respondent lived that that time.

where ENF_{kt} is the enforcement intensity in state k at time t. This index reflects the expected pressure of incoming workers into state i arising from enforcement increases in other states, based on historical migration patterns of the full employed population.

We include ENF_{it}^{IN} as an additional control in our baseline trade regression. By doing so, we isolate enforcement impacts that operate through worker inflows. If the coefficient on ENF_{it}^{IN} is small or statistically insignificant, we conclude that inflows driven by other states' enforcement do not drive our main results. Conversely, a sizable and significant coefficient would indicate that part of the enforcement effect on trade operates via these inflows rather than through other channels.

By employing this inflow index in robustness checks, we show that our estimated coefficient α on ENF_{it} remains stable even after accounting for potential inflows of workers from other states. This confirms that the enforcement effects we identify are not driven solely by relocation of labor from other jurisdictions.

The results indicate that domestic trade flows are not meaningfully shaped by worker inflows. In Table A7, the coefficient on the worker inflow measure is consistently small and statistically insignificant across both exports and imports. For interstate exports, enforcement remains negative and highly significant, with estimates ranging from –0.225 to –0.314 depending on normalization, and these results are unaffected by including the inflow control. For interstate imports, enforcement remains positive and significant, with coefficients between 0.191 and 0.251, again showing stability across specifications. The inflow control itself is imprecisely estimated and does not exhibit systematic effects. These findings suggest that relocation of workers displaced by enforcement elsewhere does not materially alter domestic trade in fruits and vegetables, and the main results are instead driven by local labor supply constraints.

In contrast, international trade outcomes show only weak evidence of a role for worker inflows. As reported in Table A8, the inflow measure is positive for foreign exports (around 1.05) but imprecisely estimated and statistically insignificant, while enforcement itself remains negative but small in magnitude and non-significant. For foreign imports, the inflow measure is negative (−1.42) but again statistically insignificant, whereas enforcement is consistently positive and significant across specifications, with coefficients between 0.121 and 0.162. These results imply that international trade responses are not systematically mediated by worker inflows. Instead, the effects of immigration enforcement on international trade appear to operate primarily through local labor supply shocks, with enforcement increasing reliance on foreign imports and dampening exports, rather than through displacement-induced inflows of workers from other states.

6.2 Falsification Tests

In the primary analysis of the effects of immigration enforcement, I used the FAF-5 data, precisely the sample of product code "03" which includes labor-intensive commodities like fruits and vegetables. In this section, I run regressions and show results for the trade flows of agricultural commodities that are not highly labor-intensive. For this, I use the sample of cereal grain crops, animal feed, milled grain products, and other prepared food (product codes "02", "04", "06", and "07" respectively) from the FAF-5 data. Although I call it falsification tests, it should be noted that the production of these crops may still require some labor, so they cannot be taken as pure placebo commodities.

Appendix Table A9 and Table A10 show the effects of immigration enforcement on the interstate and international trade for these commodities, respectively. Column (4) in both tables illustrates the results from my preferred model with the fixed effects and control variables. Throughout both tables, for the entire set of regressions, I do not see any statistically significant effects of immigration enforcement intensity on interstate exports or imports, suggesting that the impacts observed for fruits and vegetables are not a general feature of all agricultural commodities but are instead concentrated in labor-intensive production.

6.3 Addressing the Potential Endogeneity of Enforcement

A key endogeneity concern is that the adoption and intensity of state-level immigration enforcement policies may not be random, but instead correlated with agricultural or trade conditions. If states with larger agricultural sectors, greater dependence on immigrant labor, or particular trade patterns were systematically more likely to implement tougher enforcement earlier or at higher levels, then estimates of the causal effect of enforcement on fruit and vegetable trade could be biased. For instance, states with a large agricultural sector and heavy reliance on undocumented labor may be less inclined to adopt stringent enforcement. In that case, observed trade responses might reflect pre-trends in agricultural or political fundamentals rather than the independent impact of enforcement.

To probe this concern, I follow a strategy similar to Ferrara et al. (2012) and Amuedo-Dorantes et al. (2018) by examining the relationship between various pre-treatment characteristics and the adoption of immigration policies at the state level. Specifically, I construct a variable that identifies the year each state's enforcement index first became positive and regress this measure on a set of state-level characteristics measured in 2002, prior to the adoption of stricter policies. In addition, I examine whether the maximum enforcement intensity, as reached by 2012, can be explained by the same 2002 pre-treatment factors, providing a complementary check on whether the eventual strength of enforcement is systematically related to initial conditions. Finally, as an additional robustness exercise, I re-estimate these regressions using the percentage changes in key characteristics between 1997 and 2002 as regressors, to test whether pre-trends rather than levels predict enforcement adoption and intensity.

The results, reported in Appendix Table A11, indicate that the unemployment rate, the population of likely undocumented immigrants, and agricultural and trade flows in the baseline period, as well as their pre-treatment trends, do not systematically predict the timing or maximum intensity of enforcement adoption. Instead, the clearest patterns come from geography and politics: states located closer to Mexico adopt enforcement earlier and at higher intensity, while Republican vote share shows statistically significant effects in the change regressions. Interestingly, however, after controlling for other variables, the direction of the relationship between Republican share and the outcome variables does not align with the conventional narrative. Increases in Republican support between 1997 and 2002 are associated with later adoption and lower maximum intensity. This counterintuitive result suggests that partisan alignment alone does not explain policy rollout, which was shaped instead by federal initiatives.

Second, I perform a Granger-type analysis by including future policy variables in the model (Granger, 1969). If current enforcement levels drive changes in agricultural outcomes, then future levels of interior immigration enforcement should not be related to current outcomes (Angrist and Pischke, 2009). I run a set of regressions specified in equation 18, where, along with the contemporaneous enforcement variable, I also include a term that averages state-level enforcement over the three subsequent years. Using an average rather than three separate lead indicators reduces noise and multicollinearity, providing a more parsimonious falsification test while still capturing the possibility of systematic pre-trends in enforcement.

Appendix Table A12 shows no evidence of pre-trends: across both interstate and international trade specifications, the coefficients on the lead enforcement terms are consistently small and statistically insignificant. This indicates that future changes in immigration enforcement are not systematically related to current trade outcomes, reducing concerns that anticipatory behavior drives the main results.

7 Conclusion

This paper shows that U.S. interior immigration enforcement, by tightening the supply of low-skilled farm labor, functions as a de facto trade policy in labor-intensive agriculture. Using variation in enforcement intensity across states between 1997 and 2012, I find that stricter enforcement reduces the sales of labor-intensive crops. This effect reverberates through trade flows: states with stricter enforcement export less to domestic partners, import more from them, and rely more heavily on foreign imports. While international export declines are imprecisely estimated, the evidence indicates that enforcement erodes U.S. comparative advantage in horticultural products.

The results highlight that immigration enforcement does not simply affect local labor markets but reshapes the geography of agricultural trade. Domestic trade networks partially buffer the shock by reallocating produce from states with lower enforcement to those with higher enforcement, but this substitution is incomplete. On the international margin, the U.S. increasingly depends on imports, especially from Mexico, to compensate for domestic shortfalls. In this way, immigration enforcement shifts the balance of agricultural trade, amplifying long-term trends of rising imports and widening trade deficits in fruits and vegetables.

More broadly, the findings speak to ongoing debates about how labor market institutions and shocks shape competitiveness in tradable sectors. While previous work has largely emphasized technology, finance, or regulation, this study demonstrates that labor supply shocks alone can meaningfully alter trade outcomes. The implications extend beyond agriculture: any sector heavily reliant on low-skilled or migrant labor may see its export capacity constrained by restrictive policies. For policymakers, the results underscore that enforcement initiatives aimed at immigration control can generate unintended consequences for trade, food security, and resilience, reminding us that the design of labor policy is deeply intertwined with the structure of international competitiveness.

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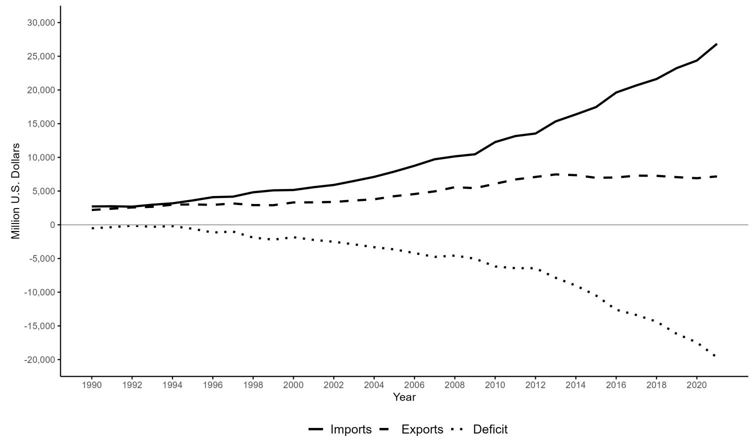
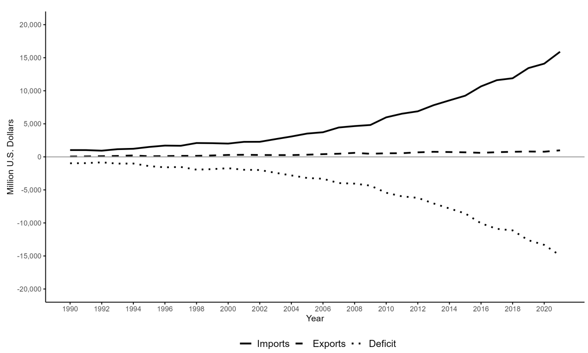
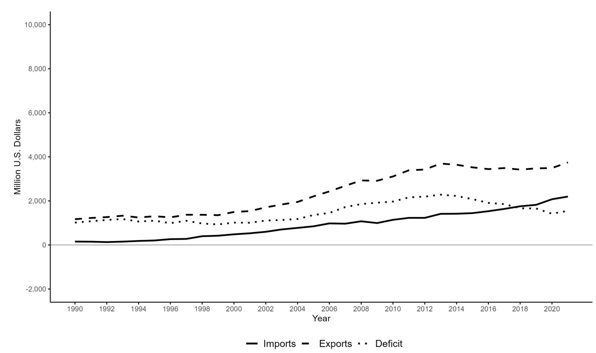
Figures



(a) Total fresh fruit and vegetable trade with foreign partners, 1990-2021



(b) Fresh fruit and vegetable trade with Mexico, 1990-2021

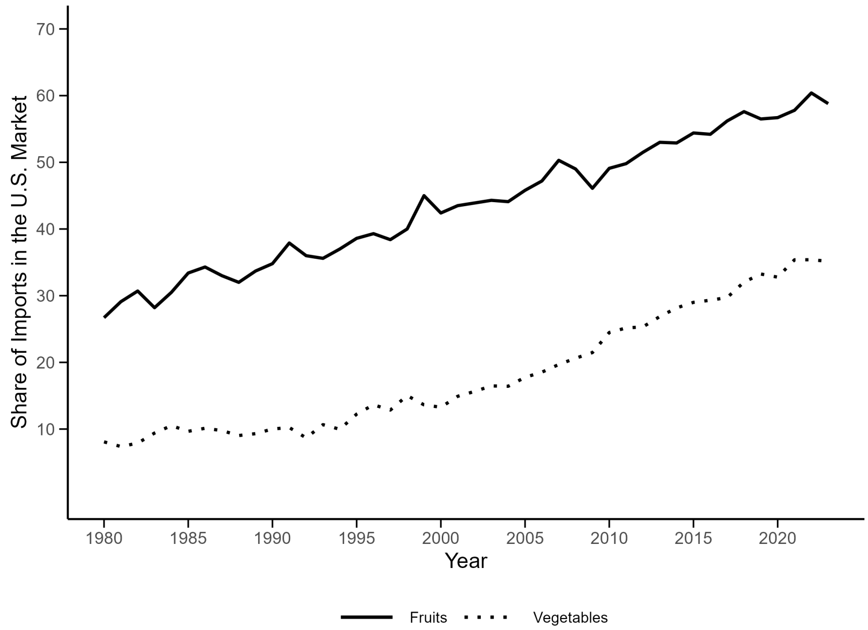


(c) Fresh fruit and vegetable trade with Canada, 1990-2021

Figure 1: Trends in U.S. Fruit and Vegetable Exports and Imports

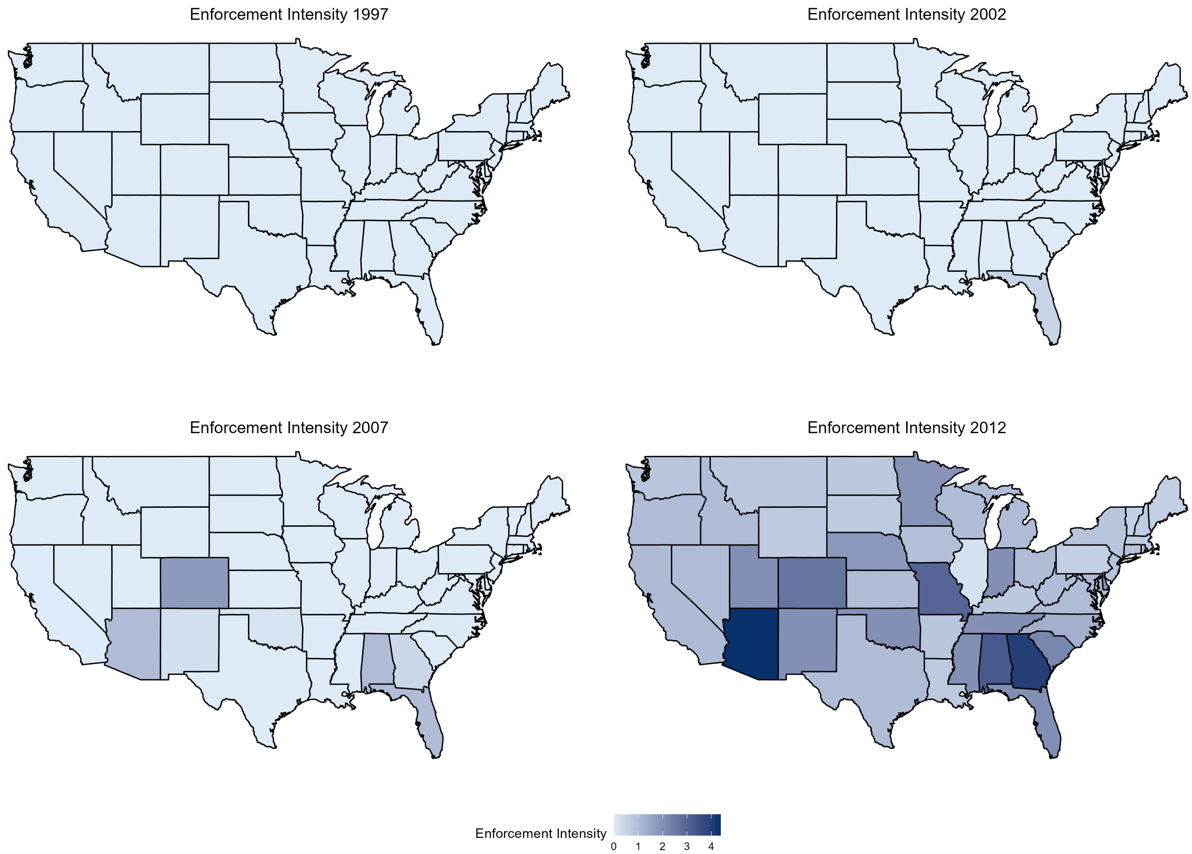
Notes: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 2: Imports as a share of U.S. fresh fruit and vegetable availability, 1981-23

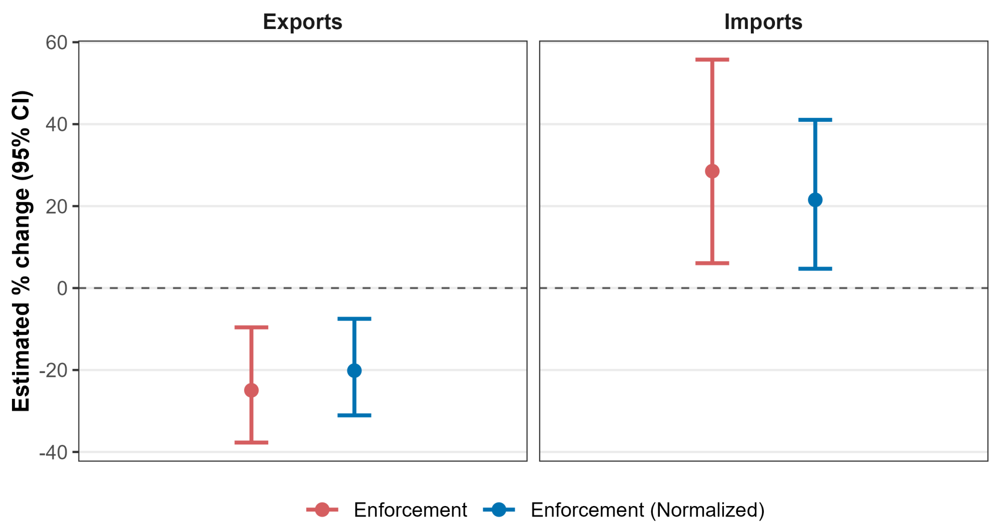


Note: Created using the data from the USDA.

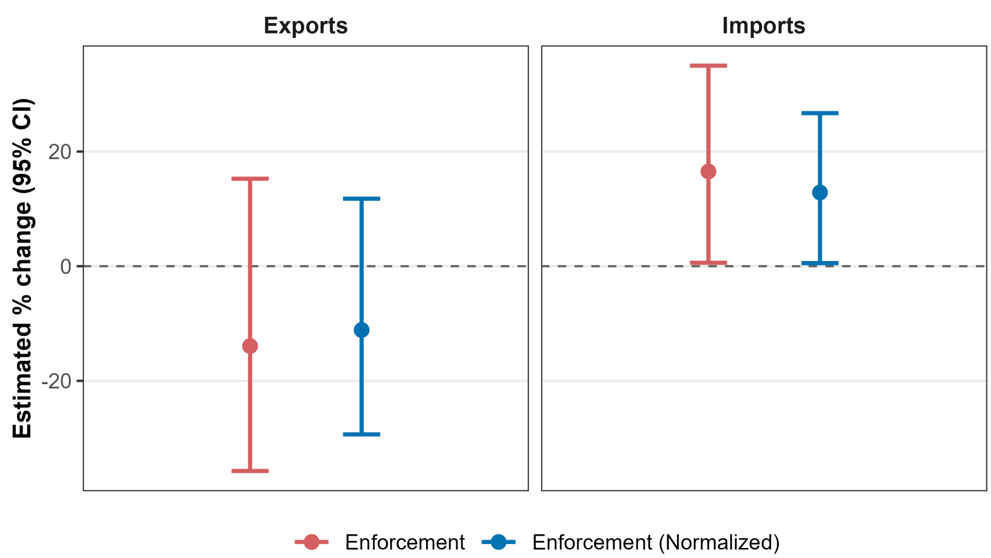
Figure 3: Spatiotemporal Variations in Enforcement intensity



Note: This figure shows the enforcement intensity across 48 contiguous U.S. states for 1997, 2002, and 2007, and 2012. The enforcement intensity variable is created using equations (15) and (16).



(a) Interstate Trade



(b) International Trade

Figure 4: Effects of Immigration Enforcement on Interstate and International Trade Flows

Note: Points show percent effects that are equivalent to the PPML estimates shown in Tables 3 and 2, and computed as $100[\exp(\hat{\beta}) - 1]$. Whiskers show 95% confidence intervals computed as $100[\exp(\hat{\beta} \pm 1.96\,\widehat{se}) - 1]$. "Enforcement (Normalized)" is a one standard deviation change in the index.

Tables

Table 1: Effects on Labor Expenses and Agricultural Production

	Labor Exp %	Labor Exp	FV Sales
	(1)	(2)	(3)
Panel A: Summary index			
Enforcement	-0.033*	-0.098***	-0.088***
	(0.016)	(0.036)	(0.029)
Panel B: Normalized summary index			
Enforcement	-0.026**	-0.076***	-0.069***
	(0.012)	(0.027)	(0.022)
Control variables	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	164	164	118

The outcome variable for column (1) is the total labor expenses (hired and contract) as a percentage of the total operating costs; for column (2) is the total agricultural labor expenses (hired and contract) in 2012 dollars; and for column (3) is the total sales of fruits, nuts, and vegetables, all taken from the Census of Agriculture from USDA National Agricultural Statistical Service (NASS). The primary explanatory variable for Panel A is the summation index created in equation (16), and that for Panel B is the normalized version of the index. All regressions are weighted by the baseline value for fruits, nuts, and vegetables production at the state level. Each regression is weighed by the baseline value of the variable at the state level. For all regressions, standard errors are clustered at the state level. *** 0.01, ** 0.05, * 0.1.

Table 2: Effects on Domestic (Interstate) Trade

	Trade (Monetary Value)			
	(1)	(2)	(3)	(4)
Panel A: Domestic Exports				
Enforcement	-0.184***	-0.194***	-0.187***	-0.287***
	(0.061)	(0.062)	(0.060)	(0.095)
Panel B: Domestic Exports (Normalized)				
Enforcement (Normalized)	-0.144***	-0.152***	-0.146***	-0.225***
	(0.048)	(0.048)	(0.047)	(0.075)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Destination-Year Fixed Effects	Yes	Yes	Yes	No
N	8,392	8,392	8,392	8,392
Panel C: Domestic Imports				
Enforcement	0.104*	0.163***	0.163***	0.251**
	(0.053)	(0.057)	(0.057)	(0.098)
Panel D: Domestic Imports (Normalized)				
Enforcement (Normalized)	0.081*	0.126***	0.126***	0.195**
	(0.041)	(0.044)	(0.044)	(0.076)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	8,392	8,392	8,392	8,392

Notes: The outcome variables are bilateral exports from a U.S. state to other U.S. states, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Export regressions (Panels A–B) include destination-year fixed effects; import regressions (Panels C–D) include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects. Column (2) adds controls for local labor-demand shocks and weighted state-level weather variables. Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3: Effects on International Trade

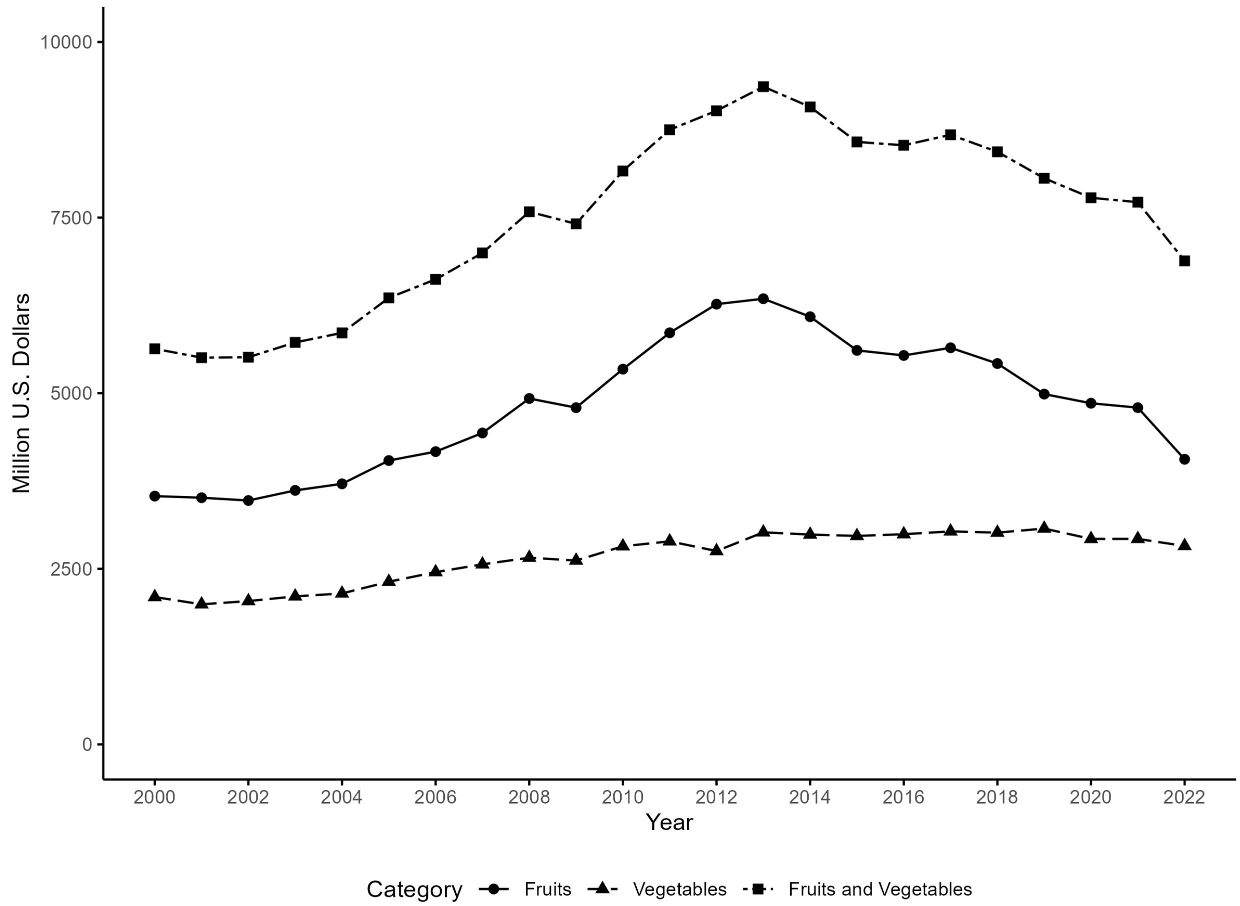
	Trade (Monetary Value)			
	(1)	(2)	(3)	(4)
Panel A: Foreign Exports				
Enforcement	-0.335*	-0.268*	-0.274*	-0.150
	(0.187)	(0.151)	(0.151)	(0.149)
Panel B: Foreign Exports (Normalized)				
Enforcement (Normalized)	-0.263*	-0.210*	-0.216*	-0.118
	(0.147)	(0.119)	(0.119)	(0.117)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Destination-Year Fixed Effects	Yes	Yes	Yes	No
N	1,524	1,524	1,524	1,524
Panel C: Foreign Imports				
Enforcement	-0.013	-0.036	-0.009	0.153**
	(0.035)	(0.037)	(0.051)	(0.075)
Panel D: Foreign Imports (Normalized)				
Enforcement (Normalized)	-0.010	-0.029	-0.007	0.121**
	(0.028)	(0.029)	(0.041)	(0.059)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	1,536	1,536	1,536	1,536

Notes: The outcome variables are bilateral exports from a U.S. state to foreign regions, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Export regressions (Panels A–B) include destination-year fixed effects; import regressions (Panels C–D) include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects. Column (2) adds controls for local labor-demand shocks and weighted state-level weather variables. Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

APPENDICES

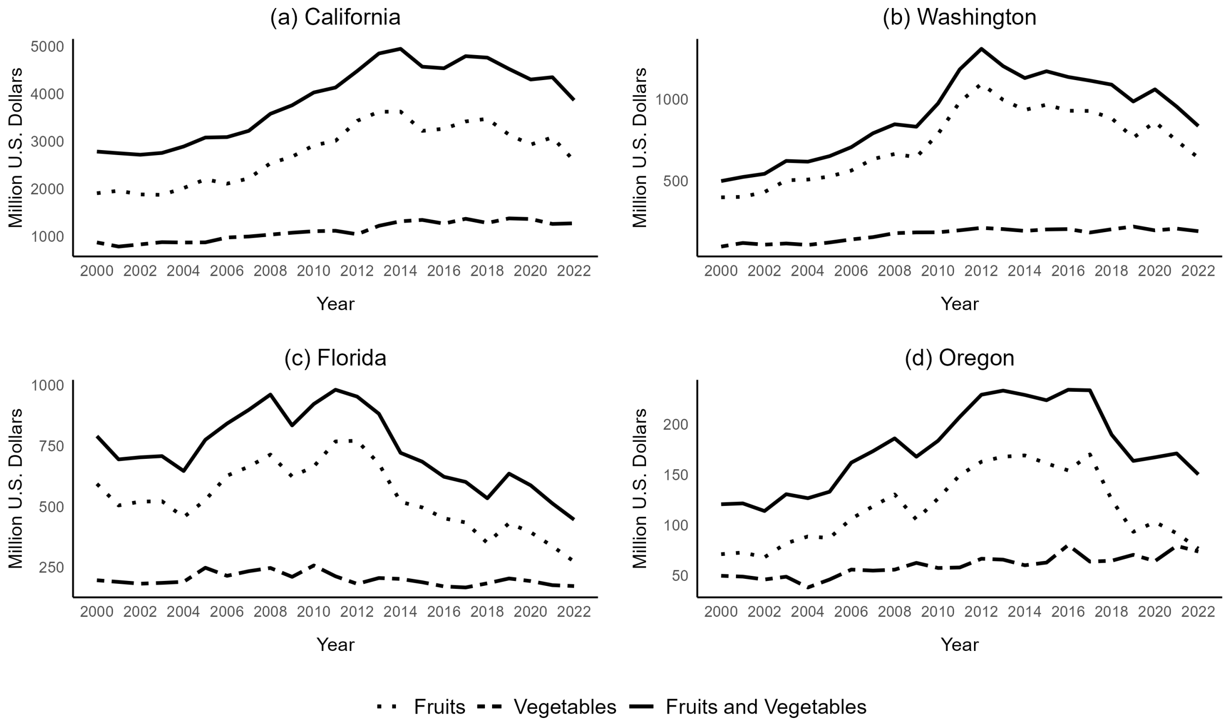
A Other Figures

Figure 5: Fresh fruit and vegetable trade with Canada, 1990-2021



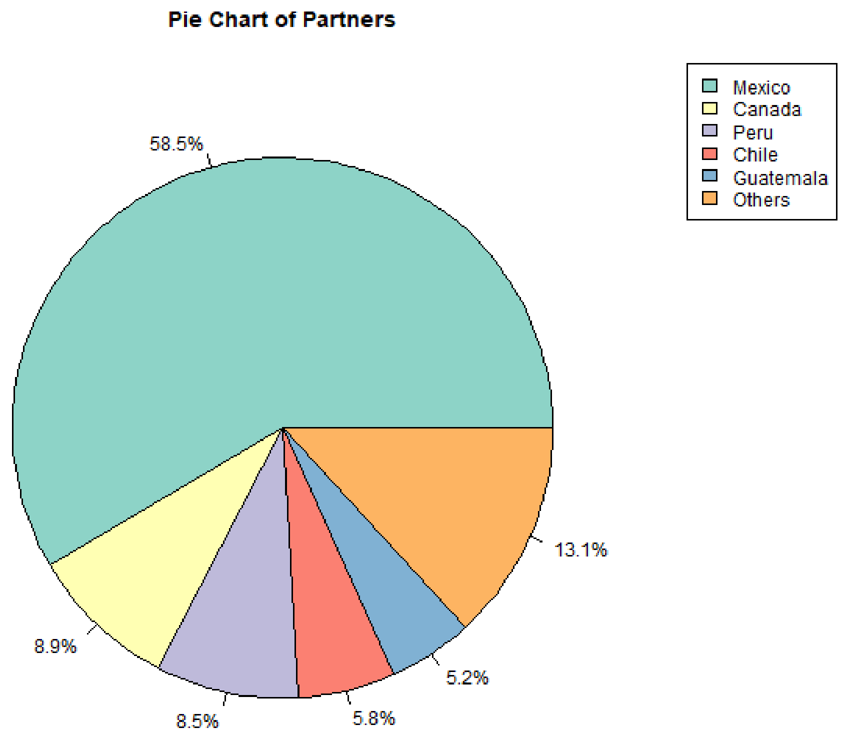
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 6: Fresh fruit and vegetable exports, Four Largest Exporters, 2000-2022



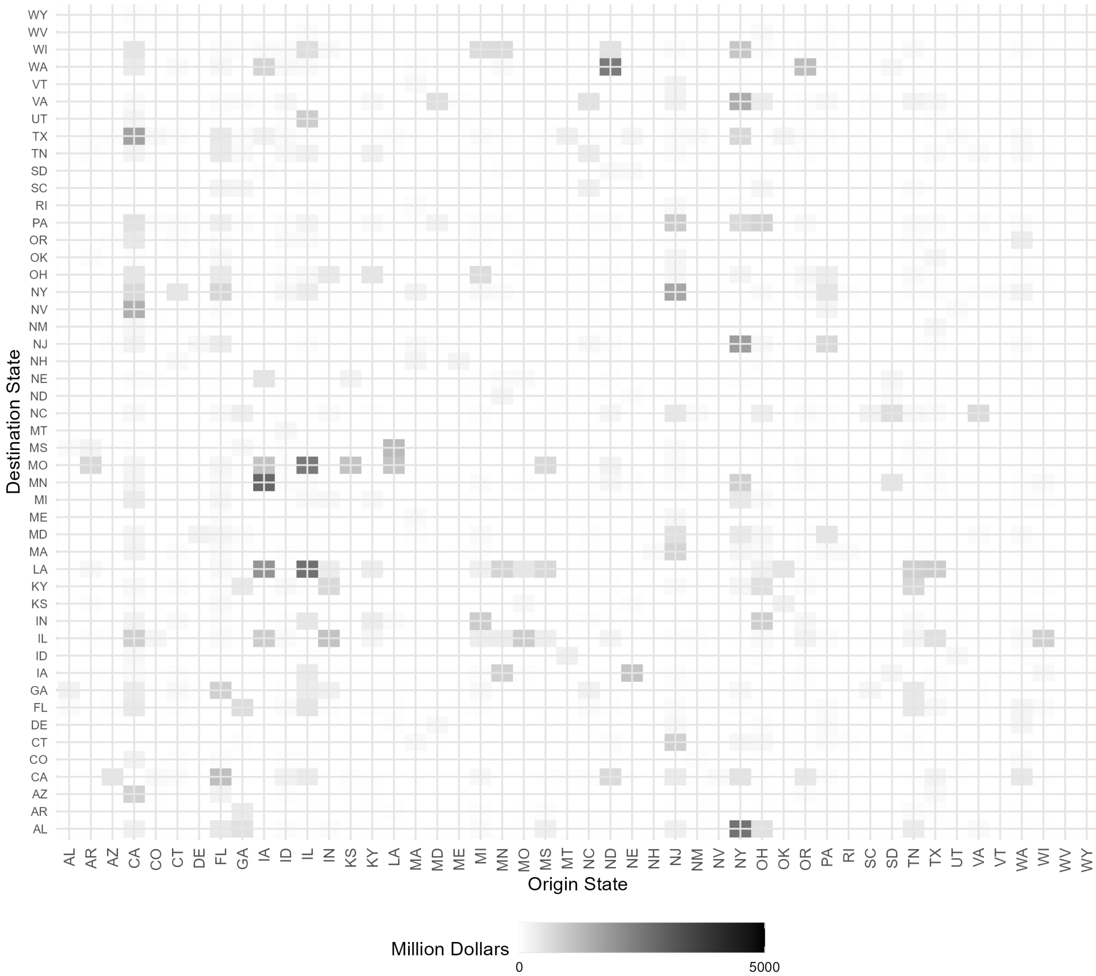
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 7: Import partners for fresh fruits and vegetables for the United States, 2022



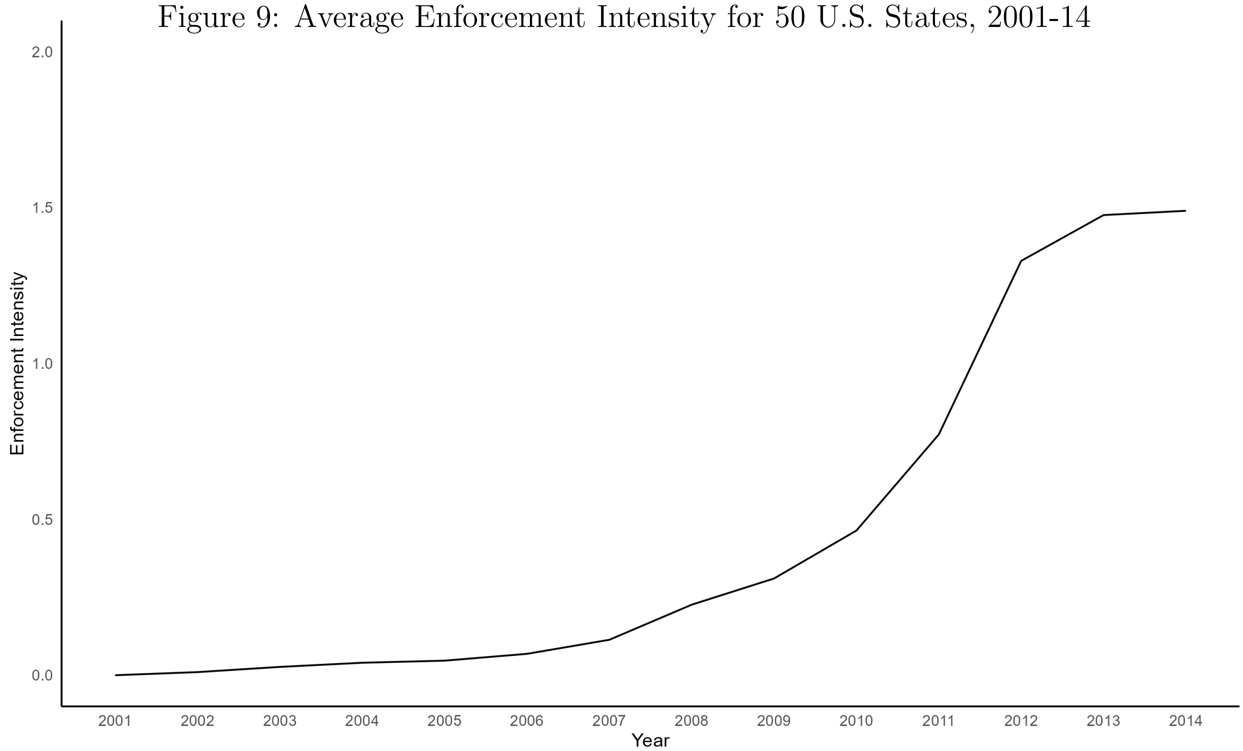
Note: Data comes from the USDA FSA.

Figure 8: Domestic Interstate Trade, in Million Dollars, 2012



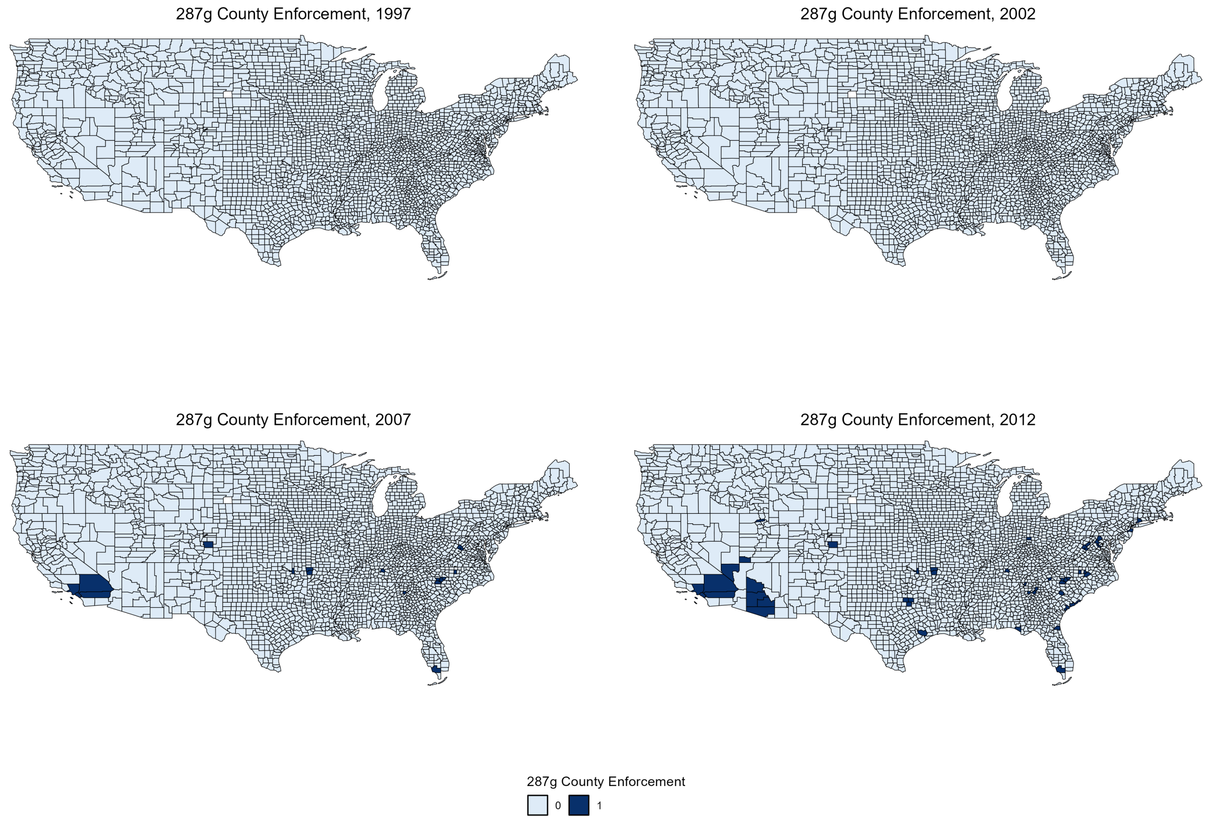
Note: Created using the data from the Freight Analysis Framework (FAF-5). The values are in 2022 US Dollars.

Figure 9: Average Enforcement Intensity for 50 U.S. States, 2001-14



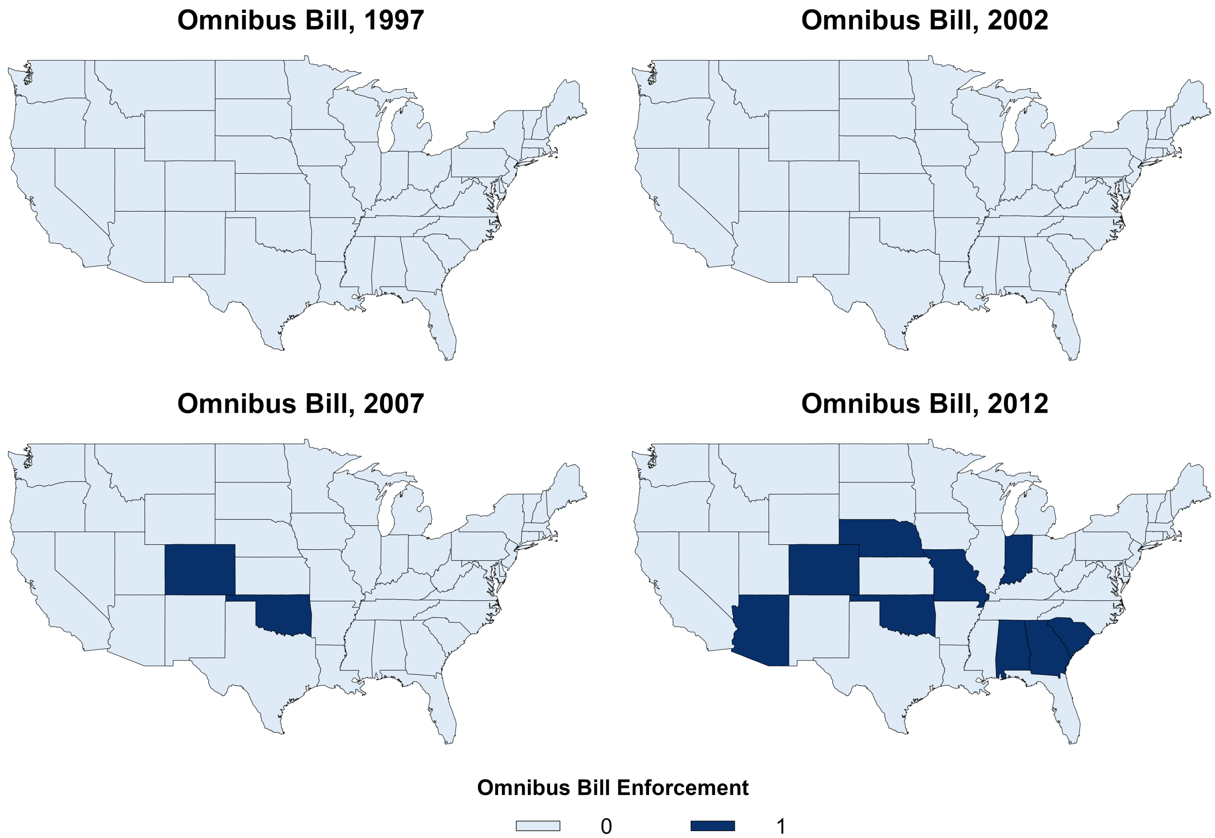
Note: This figure shows the average enforcement intensity across 50 U.S. states from 2001 to 2014. The enforcement intensity variable is created using equations (15) and (16).

Figure 10: Spatiotemporal Variations in 287g County Enforcement



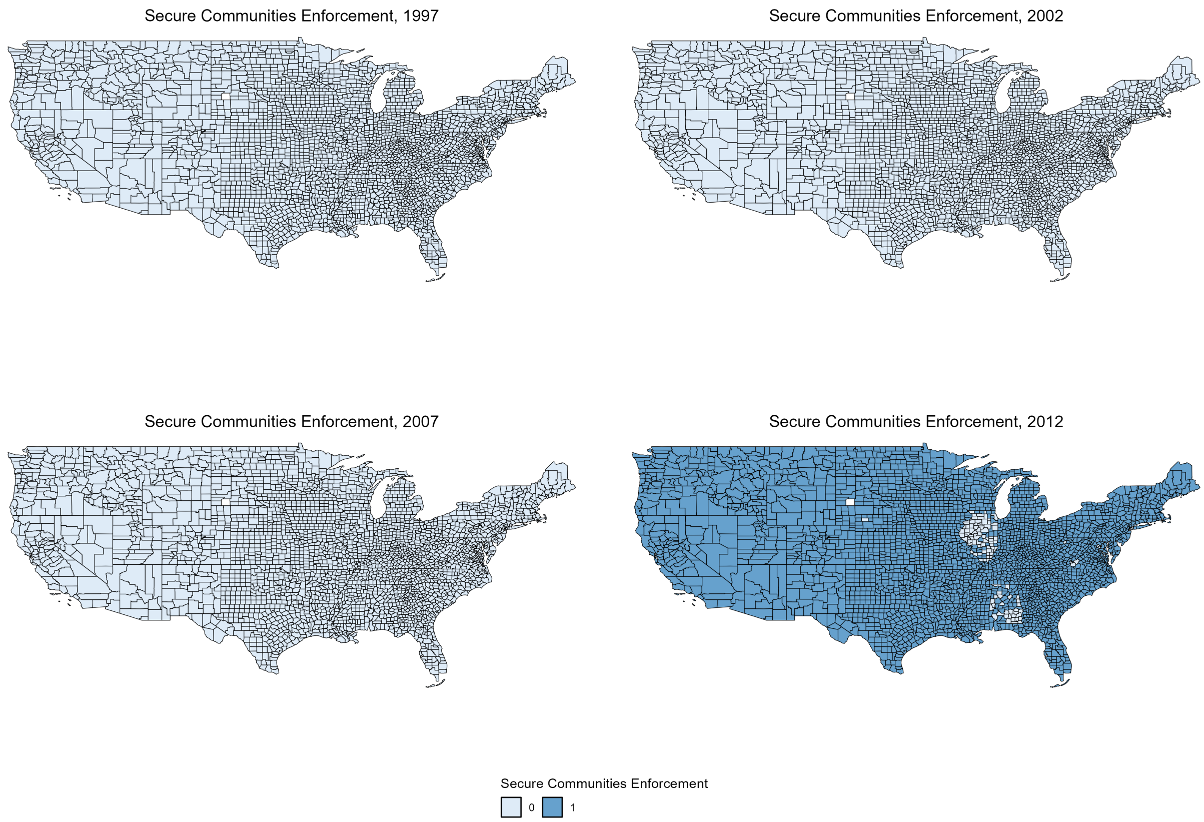
Note: This figure shows counties with active Immigration and National Act 287g county-level policy across 50 U.S. states for 1997, 2002, and 2007, and 2012.

Figure 11: Spatiotemporal Variations in Omnibus Bill Enforcement



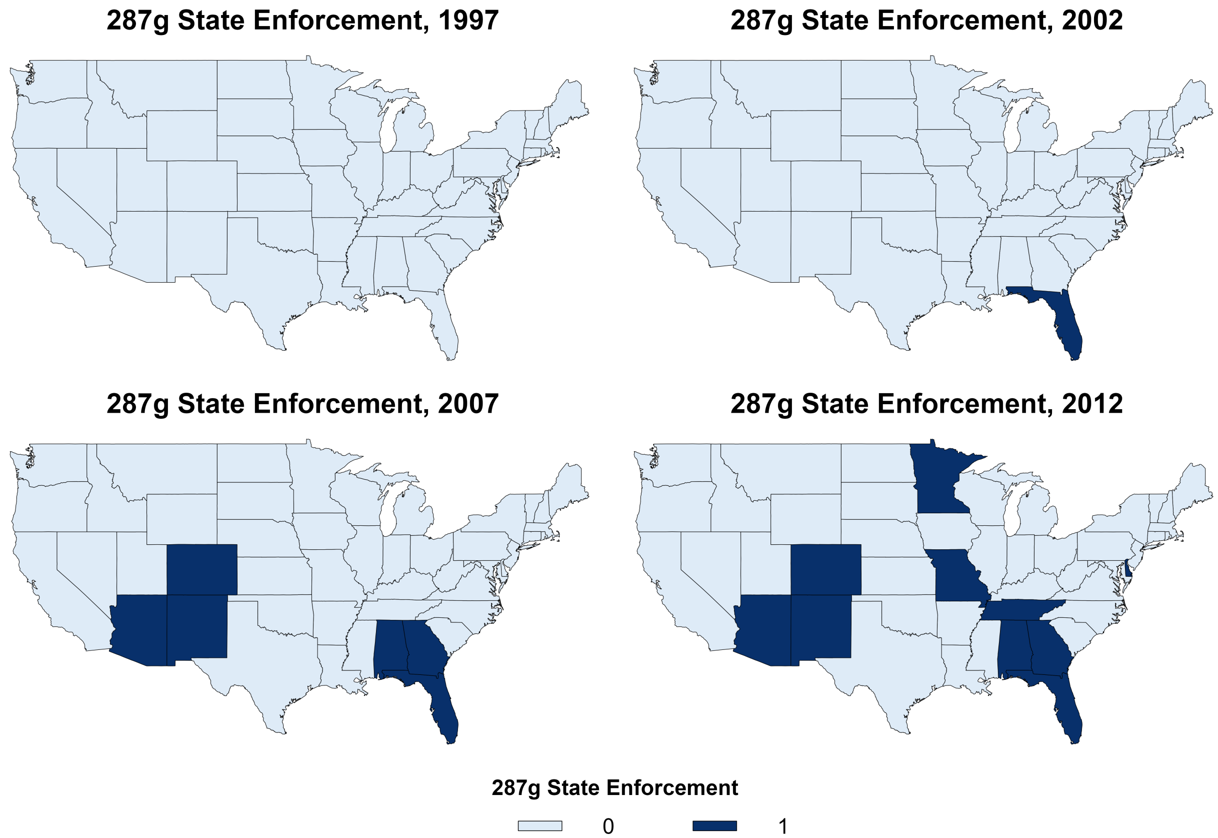
Note: This figure shows counties with active Omnibus Bill across 50 U.S. states for 1997, 2002, and 2007, and 2012.

Figure 12: Spatiotemporal Variations in Secure Communities Enforcement



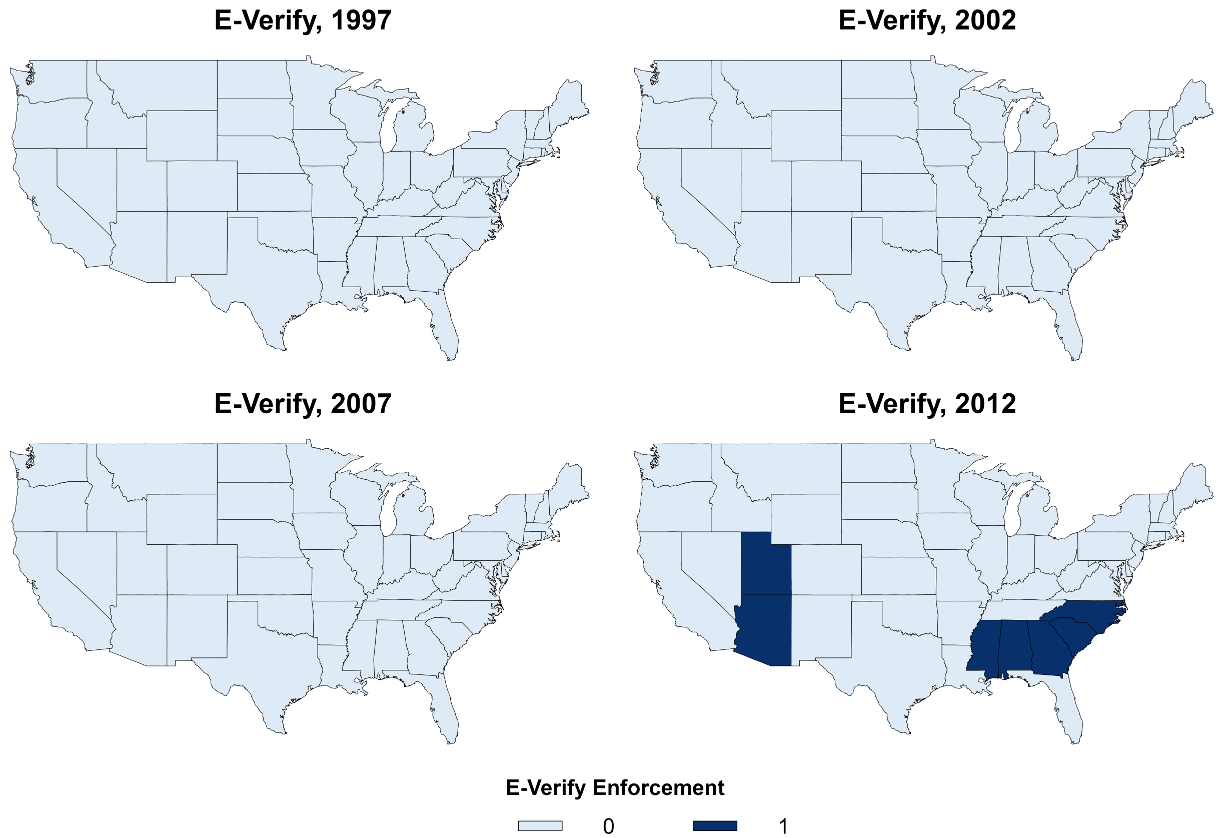
Note: This figure shows counties with active Secure Communities policy across 50 U.S. states for 1997, 2002, and 2007, and 2012.

Figure 13: Spatiotemporal Variations in 287g State Enforcement



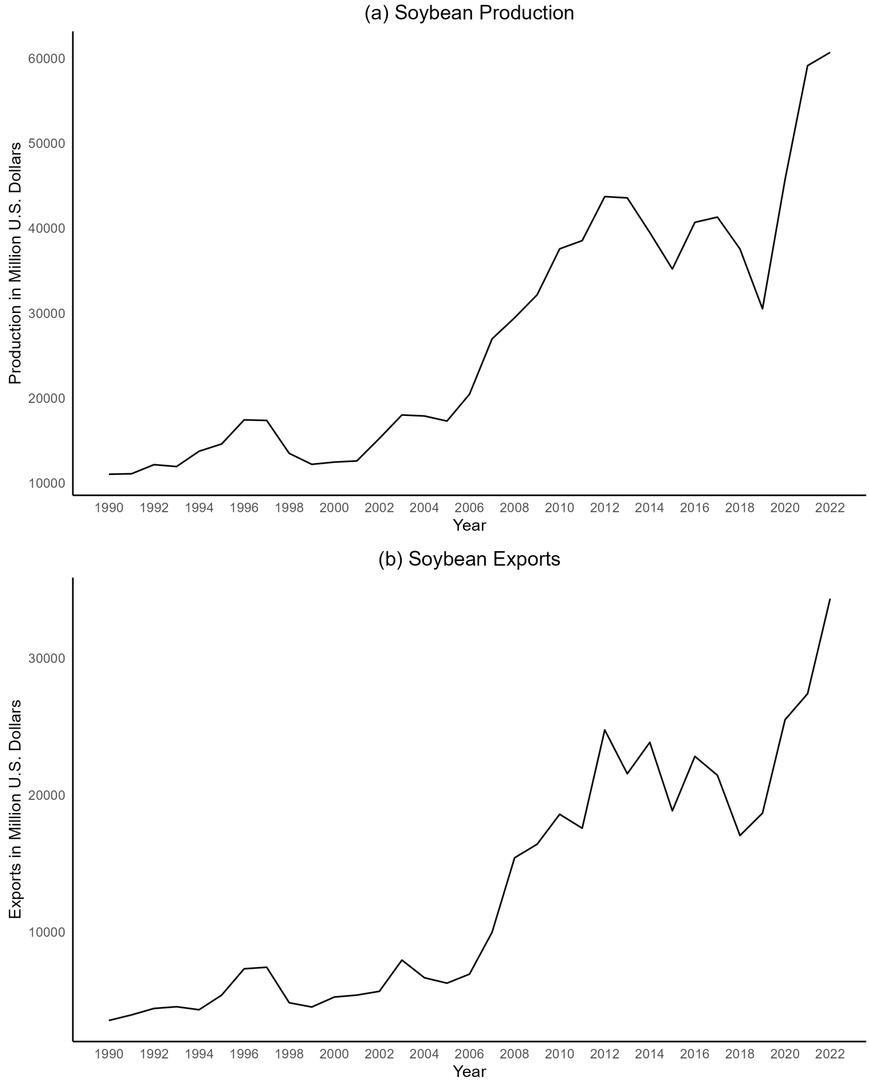
Note: This figure shows counties with active state-level 287g policy across 50 U.S. states for 1997, 2002, and 2007, and 2012.

Figure 14: Spatiotemporal Variations in E-Verify Enforcement



Note: This figure shows counties with active E-Verify policy across 50 U.S. states for 1997, 2002, and 2007, and 2012.

Figure 15: Soybean Production and Exports, 1990-2022



Note: This figure shows the total soybean production and exports from 1990-2022. All values are adjusted to 2022 dollars.

B Other Tables

Table A1: Interior Immigration Enforcement Policies: Key Features

	287(g) – State MOA	287(g) – County/City MOA	Secure Communities	E-Verify	Omnibus Laws
Policy type	Police-based (state agency with ICE)	Police-based (local MOA with ICE)	Police-based biometric checks at booking	Employer-based work verification	Mixed (police + admin)
Implementing authority	DHS/ICE + state police or DOC	DHS/ICE + sheriff or city police	DHS/ICE + FBI databases	USCIS (DHS) + SSA; employers	State legislatures
Jurisdiction level	State agency facilities	County/city jails or field ops	Nationwide jails (by county rollout)	Nationwide; state/federal mandates	Statewide (varies by law)
Implementation period	2000s onward; renew/terminate	2002–2010 main wave	2008–2013 rollout; later changes	Pilot 1990s; internet-based mid-2000s	Mid-2000s–2010s
Coverage	Few states; scope varies	Hundreds of local MOAs at peak	Nearly all counties by 2013	All states; federal contractors required; some state mandates	Subset of states; provisions differ
Mechanism	Trained state officers detain/screen	Local officers screen, warrants, detainers	Fingerprints shared with DHS; ICE notified	I-9 data checked vs. SSA/DHS online	Police checks; limits on benefits, licenses
Targets	Arrestees in state custody	Arrestees in local custody	All arrestees booked in jails	All new hires (where required)	Undocumented residents statewide
Mandate status	Voluntary MOA with ICE	Voluntary MOA with ICE	Federal program; local discretion limited	Voluntary unless mandated; federal contractors must comply	Mandatory within adopting states
Measurement in research	Indicator of MOA start; scope by bookings covered	Indicator of MOA start; jail population share	County-by-date adoption; coverage by pop	State mandate timing; contractor mandate	State-by-date omnibus index
Design caveats	Heterogeneous MOA terms; selective adoption	Jail vs. field models differ; political endogeneity	Staggered rollout; admin changes	Non-random employer use; compliance gaps	Multi-provision; hard to isolate effects

Notes: MOA = Memorandum of Agreement under INA 287(g). DOC = Department of Corrections. Text shortened for compact presentation.

Table A2: Effects on Domestic (Interstate) Trade

	Trade (Monetary Value)			
	(1)	(2)	(3)	(4)
Panel A: Domestic Imports				
Enforcement	0.272***	0.335***	0.334***	0.407***
	(0.105)	(0.103)	(0.103)	(0.115)
Enforcement × High Exporter Enforcement	-0.278**	-0.287***	-0.286***	-0.279***
	(0.118)	(0.110)	(0.110)	(0.099)
Panel B: Domestic Imports (Normalized)				
Enforcement	0.212***	0.260***	0.260***	0.317***
	(0.082)	(0.080)	(0.080)	(0.089)
Enforcement × High Exporter Enforcement	-0.216**	-0.223***	-0.222***	-0.217***
	(0.091)	(0.085)	(0.085)	(0.077)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	8,392	8,392	8,392	8,392

Notes: The outcome variables are bilateral imports from a U.S. state to other U.S. states, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is immigration enforcement in Panels A is the summation index defined in equation (16) and that in Panels B is its normalized version. High Export Enforcement variable equals 1 if the state's maximum enforcement intensity (in 2012) is above the median value. The regressions include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects. Column (2) adds controls for local labor-demand shocks and weighted state-level weather variables. Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A3: Effects on International Imports from Mexico and Canada

	Trade (Monetary Value)			
	(1)	(2)	(3)	(4)
Panel A: Imports from Mexico				
Enforcement	-0.028	-0.067***	-0.015	0.297**
	(0.031)	(0.025)	(0.077)	(0.150)
Panel B: Imports from Mexico (Normalized)				
Enforcement (Normalized)	-0.022	-0.051***	-0.012	0.229**
	(0.023)	(0.019)	(0.059)	(0.116)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	192	192	192	192
Panel C: Imports from Canada				
Enforcement	-0.004	0.005	-0.002	0.054
	(0.093)	(0.091)	(0.097)	(0.108)
Panel D: Imports from Canada (Normalized)				
Enforcement (Normalized)	-0.003	0.004	-0.001	0.041
	(0.072)	(0.070)	(0.074)	(0.083)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	192	192	192	192

Notes: The outcome variables are bilateral imports into U.S. states from Mexico or Canada, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is immigration enforcement: Panels A and C use the summation index defined in equation (16); Panels B and D use its normalized version. Panels A–B report imports from Mexico; Panels C–D report imports from Canada. All regressions estimate a reduced-form gravity model via PPML. All specifications include origin-year fixed effects, origin–destination (dyad) fixed effects, and controls (local labor-demand shocks and weighted state-level weather variables). Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin–destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A4: Effects on International Exports: Excluding and Only Including Top 10 Soybean Producing States

	Trade (Monetary Value)			
	(1)	(2)	(3)	(4)
Panel A: Excluding top 10 soybean producing states				
Enforcement	-0.377*	-0.257*	-0.290*	-0.198
	(0.205)	(0.151)	(0.173)	(0.177)
Panel B: Excluding top 10 soybean producing states (Treatment normalized)				
Enforcement (Normalized)	-0.296*	-0.202*	-0.228*	-0.155
	(0.161)	(0.119)	(0.136)	(0.139)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Destination-Year Fixed Effects	Yes	Yes	Yes	No
N	1,172	1,172	1,172	1,172
Panel C: Only including top 10 soybean producing states				
Enforcement	-0.409***	-0.355*	-0.243*	0.080
	(0.159)	(0.185)	(0.129)	(0.148)
Panel D: Only including top 10 soybean producing states (Treatment normalized)				
Enforcement (Normalized)	-0.321***	-0.279*	-0.191*	0.062
	(0.125)	(0.145)	(0.102)	(0.116)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Destination-Year Fixed Effects	Yes	Yes	Yes	No
N	320	320	320	320

Notes: The outcome variables are bilateral exports from a U.S. state to foreign trade partners, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Panels A–B include sample of U.S. states as exporters excluding top 10 largest soybean producing states. Panels C–D include sample of U.S. states as exporters only including top 10 largest soybean producing states. All specifications include destination-year and origin–destination (dyad) fixed effects. Column (2) adds controls for local labor-demand shocks and weighted state-level weather variables. Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A5: Effects on International Trade

	Monetary Value	
	(1)	(2)
Enforcement	-0.663	-0.640
	(0.774)	(0.785)
Domestic Import Partners' Enforcement		0.260
× State with Prominent Port for FVs		(0.362)
Control Variables	Yes	Yes
Partners' Enforcement Control	Yes	Yes
Dyadic Fixed Effects	Yes	Yes
Destination-Year Fixed Effects	Yes	Yes
State-specific Linear Trends	Yes	Yes
N	1,364	1,364

Notes: The outcome variables are bilateral exports from a U.S. state to foreign regions, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is the normalized version of the immigration enforcement. Both regressions estimate a reduced-form gravity model via PPML. Both specifications include origin–destination (dyad) fixed effects, destination-year fixed effects, and control variables, including a measure for local labor-demand shocks, weighted state-level weather variables. Column, partner states' enforcement intensity weighted by baseline trade flows, and state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A6: Effects on International Trade

	Monetary Value	
	(1)	(2)
Enforcement	0.020	-0.015
	(0.078)	(0.077)
Domestic Export Partners' Enforcement		0.270***
		(0.085)
Control Variables	Yes	Yes
Partners' Enforcement Control	Yes	Yes
Dyadic Fixed Effects	Yes	Yes
Origin-Year Fixed Effects	Yes	Yes
State-specific Linear Trends	Yes	Yes
N	1,408	1,408

Notes: The outcome variables are bilateral imports from a U.S. state to foreign regions, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The key explanatory variable is the normalized version of the immigration enforcement. Both regressions estimate a reduced-form gravity model via PPML. Both specifications include origin–destination (dyad) fixed effects, origin-year fixed effects, and control variables, including a measure for local labor-demand shocks, weighted state-level weather variables. Column, partner states' enforcement intensity weighted by baseline trade flows, and state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A7: Effects on Interstate Trade

	Monetary Value	
	(1)	(2)
Panel A: Interstate Exports		
Enforcement	-0.287***	-0.314***
	(0.095)	(0.094)
Worker Inflow Measure		-0.588
		(0.514)
Panel B: Interstate Exports (Normalized)		
Enforcement	-0.225***	-0.245***
	(0.075)	(0.074)
Worker Inflow Measure		-0.588
		(0.514)
Controls, Fixed Effects, and Time Trends	Yes	Yes
Worker Inflow Measure Control	No	Yes
N	8,392	8,392
Panel C: Interstate Imports		
Enforcement	0.251**	0.246**
	(0.098)	(0.098)
Worker Inflow Measure		-0.476
		(0.708)
Panel D: Interstate Imports (Normalized)		
Enforcement	0.195**	0.191**
	(0.076)	(0.076)
Worker Inflow Measure		-0.476
		(0.708)
Controls, Fixed Effects, and Time Trends	Yes	Yes
Worker Inflow Measure Control	No	Yes
N	8,392	8,392

Notes: The outcome variables are bilateral trade between two U.S. states, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). Panel A and Panel B analyzes interstate exports, and Panel C and Panel D analyzes interstate imports. The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Export regressions (Panels A–B) include destination-year fixed effects; import regressions (Panels C–D) include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects and control variables, including a measure for local labor-demand shocks, weighted state-level weather variables, partner states' enforcement intensity weighted by baseline trade flows, and state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A8: Effects on International Trade

	Monetary Value	
	(1)	(2)
Panel A: Foreign Exports		
Enforcement	-0.150	-0.112
	(0.149)	(0.154)
Worker Inflow Measure		1.054
		(0.762)
Panel B: Foreign Exports (Normalized)		
Enforcement	-0.118	-0.088
	(0.117)	(0.121)
Worker Inflow Measure		1.054
		(0.762)
Controls, Fixed Effects, and Time Trends	Yes	Yes
Worker Inflow Measure Control	No	Yes
N	1,524	1,524
Panel C: Foreign Imports		
Enforcement	0.153**	0.162**
	(0.075)	(0.073)
Worker Inflow Measure		-1.422
		(1.216)
Panel D: Foreign Imports (Normalized)		
Enforcement	0.121**	0.128**
	(0.059)	(0.058)
Worker Inflow Measure		-1.422
		(1.216)
Controls, Fixed Effects, and Time Trends	Yes	Yes
Worker Inflow Measure Control	No	Yes
N	1,536	1,536

Notes: The outcome variables are bilateral trade between a U.S. states and foreign partners, measured as the total value of fruits and vegetables in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). Panel A and Panel B analyzes international exports, and Panel C and Panel D analyzes international imports. The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Export regressions (Panels A–B) include destination-year fixed effects; import regressions (Panels C–D) include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects and control variables, including a measure for local labor-demand shocks, weighted state-level weather variables, partner states' enforcement intensity weighted by baseline trade flows, and state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A9: Effects on Domestic (Interstate) Trade: Falsification Test

	Trade (Monetary Value)			
	(1)	(2)	(3)	(4)
Panel A: Domestic Exports				
Enforcement	-0.096	-0.052	-0.029	0.023
	(0.106)	(0.099)	(0.092)	(0.095)
Panel B: Domestic Exports (Normalized)				
Enforcement	-0.075	-0.041	-0.023	0.018
	(0.083)	(0.078)	(0.072)	(0.075)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Destination-Year Fixed Effects	Yes	Yes	Yes	No
N	31,608	31,608	31,608	31,608
Panel C: Domestic Imports				
Enforcement	0.057	0.057	0.047	0.100
	(0.058)	(0.057)	(0.057)	(0.073)
Panel D: Domestic Imports				
Enforcement	0.045	0.045	0.037	0.079
	(0.046)	(0.045)	(0.045)	(0.058)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	31,608	31,608	31,608	31,608

Notes: The outcome variables are bilateral exports from a U.S. state to other U.S. states, measured as the total value of placebo crops in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The placebo crops include cereal grain crops, animal feed, milled grain products, and other prepared food. The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Export regressions (Panels A–B) include destination-year fixed effects; import regressions (Panels C–D) include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects and product code fixed effects. Column (2) adds controls for local labor-demand shocks and weighted state-level weather variables. Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A10: Effects on Domestic (International) Trade: Falsification Test

	Monetary Value			
	(1)	(2)	(3)	(4)
Panel A: Domestic Exports				
Enforcement	-0.096	-0.052	-0.029	-0.041
	(0.106)	(0.099)	(0.092)	(0.095)
Panel B: Domestic Exports (Normalized)				
Enforcement (Normalized)	-0.075	-0.040	-0.022	-0.033
	(0.082)	(0.077)	(0.071)	(0.073)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Destination-Year Fixed Effects	Yes	Yes	Yes	No
N	5,960	5,960	5,960	5,960
Panel C: Domestic Imports				
Enforcement	0.057	0.057	0.047	0.053
	(0.058)	(0.057)	(0.057)	(0.060)
Panel D: Domestic Imports (Normalized)				
Enforcement (Normalized)	0.039	0.039	0.032	0.035
	(0.045)	(0.044)	(0.045)	(0.046)
Control Variables	No	Yes	Yes	Yes
Partners' Enforcement Control	No	No	Yes	Yes
State-Specific Linear Trends	No	No	No	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	No
Origin-Year Fixed Effects	Yes	Yes	Yes	No
N	5,952	5,952	5,952	5,952

Notes: The outcome variables are bilateral exports from a U.S. state to foreign regions, measured as the total value of placebo crops in *millions of 2023 U.S. dollars* from the Freight Analysis Framework (FAF-5). The placebo crops include cereal grain crops, animal feed, milled grain products, and other prepared food. The key explanatory variable is immigration enforcement: in Panels A and C we use the summation index defined in equation (16); in Panels B and D we use its normalized version. All regressions estimate a reduced-form gravity model via PPML. Export regressions (Panels A–B) include destination-year fixed effects; import regressions (Panels C–D) include origin-year fixed effects. All specifications include origin–destination (dyad) fixed effects and product code fixed effects. Column (2) adds controls for local labor-demand shocks and weighted state-level weather variables. Column (3) additionally includes partner states' enforcement intensity weighted by baseline trade flows. Column (4) additionally includes state-specific linear time trends. Robust standard errors are clustered at the origin-by-destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A11: Effects on Interstate Export of Fruits and Vegetables

	2002 Values		1997–2002 Change	
	First Adoption	Max Enforcement	First Adoption	Max Enforcement
	(1)	(2)	(3)	(4)
Unemployment rate	45.933 (42.697)	-2.661 (21.735)	22.765 (62.812)	30.434 (27.813)
Likely-undocumented population	-16.449 (33.777)	14.785 (17.560)	-91.146 (78.511)	-17.297 (46.653)
Agricultural worker population	-0.000** (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000** (0.000)
Total agricultural/crop sales	0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)	0.000 (0.000)
Agricultural wage	0.004 (0.004)	-0.001 (0.001)	0.001 (0.002)	-0.001 (0.001)
International FV exports	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
International FV imports	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.000)
Interstate FV exports	-0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)	0.000** (0.000)
Interstate FV imports	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Republican share	0.034 (0.046)	0.005 (0.022)	0.291** (0.108)	-0.084* (0.044)
Distance to Mexico	0.002*** (0.001)	-0.001* (0.000)	0.003*** (0.001)	-0.001*** (0.000)
Borders Mexico	1.629 (2.040)	0.381 (1.262)	1.635 (1.254)	0.360 (0.902)
N	48	48	48	48

Notes: The outcome variable in columns (1) and (3) is the **onset year**, defined as the first year in which a state's immigration enforcement intensity becomes positive from zero. The outcome variable in columns (2) and (4) is the peak enforcement intensity, measured by its 2012 level (the sample's peak year). Descriptions and sources for all explanatory variables appear in Appendix Section C. All specifications are estimated by ordinary least squares (OLS). Heteroskedasticity-robust standard errors are reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A12: Effects on Fruit and Vegetable Trade

	Export		Import	
	(1)	(2)	(3)	(4)
Panel A: Interstate Trade Flows				
Enforcement	-0.187***	-0.073	0.163***	0.184*
	(0.060)	(0.115)	(0.057)	(0.104)
Lead Enforcement (3-year average)		-0.141		-0.026
		(0.111)		(0.102)
Control Variables	Yes	Yes	Yes	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	Yes
Destination-Year Fixed Effects	Yes	Yes	No	No
Origin-Year Fixed Effects	No	No	Yes	Yes
N	8,392	8,392	8,392	8,392
Panel B: International Trade Flows				
Enforcement	-0.274*	-0.432*	-0.015	-0.030
	(0.151)	(0.240)	(0.037)	(0.057)
Lead Enforcement (3-year average)		0.199		0.026
		(0.150)		(0.066)
Control Variables	Yes	Yes	Yes	Yes
Dyadic Fixed Effects	Yes	Yes	Yes	Yes
Destination-Year Fixed Effects	Yes	Yes	No	No
Origin-Year Fixed Effects	No	No	Yes	Yes
N	1,492	1,492	1,536	1,536

Notes: The outcome variables are bilateral exports in columns (1) and (2), and bilateral imports in columns (3) and (4), measured as the total value of fruits and vegetables in millions of 2023 U.S. dollars from the Freight Analysis Framework (FAF-5). Panel A reports interstate trade flows; Panel B reports international trade flows. The key explanatory variable is normalized immigration enforcement. Lead enforcement (3-year average) is the mean of a state's enforcement intensity over the three years following year t (i.e., $t+1$ to $t+3$). All regressions estimate a reduced-form gravity model using PPML. All specifications include fixed effects and controls, including local labor-demand shocks, weighted state-level weather variables, and partner states' enforcement intensity weighted by baseline trade flows. Standard errors are heteroskedasticity-robust and clustered at the origin–destination (dyad) level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

C Creation of Variables for the Exogeneity Test

In Section 6.3, I test exogeneity of state-level immigration enforcement by examining how pre-treatment characteristics predict the subsequent adoption of state-level immigration policies. Table 6 reports the results. In this section, I document the variables I use. Throughout, I use either (i) the 2002 level or (ii) the percentage change from 1997 to 2002.

Unemployment rate. I construct state-level unemployment rates using the decennial Census and the American Community Survey (ACS). Because the ACS replaces the Census long form after 2000, I linearly interpolate the 1997 value from the 1990 and 2000 Censuses, and I take the 2002 value from the 2002 ACS. I define an unemployment indicator equal to one for civilian unemployed persons, excluding armed forces, and restricting to ages ≥ 16. The weighted unemployment rate is

$$\frac{\sum_i \texttt{perwt}_i \, \mathbf{1}\{\text{ESR}_i = 3,\ \text{age}_i \geq 16\}}{\sum_i \texttt{perwt}_i \, \mathbf{1}\{\text{ESR}_i \in \{1,2,3\},\ \text{age}_i \geq 16\}},$$

where `perwt` is the ACS person weight.

Likely-undocumented population. The ACS does not report legal status. I therefore construct a proxy for likely undocumented immigrants using a residual-style approach (29). Among the foreign-born, I exclude individuals with clear signals of legal status, and treat the remainder as likely undocumented. Specifically, I retain foreign-born individuals who (i) arrived after 1980, (ii) were not born in Cuba, (iii) are not veterans, (iv) report no public-assistance receipt in the past year,[26] and (v) have less than a high-school education. This measure is a proxy and should be interpreted with caution.

Agricultural worker population. I proxy the agricultural workforce using the Quarterly Census of Employment and Wages (QCEW). I aggregate county employment in agriculture-related industries (NAICS 11) to the state level.

Total agricultural/crop sales. I take state-level agricultural and crop sales from the Census of Agriculture.

Agricultural wage. I compute the average wage in agriculture from QCEW earnings and employment (state-year).

Trade variables. I obtain bilateral state-to-state fruit and vegetable trade flows from the Freight Analysis Framework (FAF-5).

Republican vote share. I measure the state-level Republican share using Dave Leip's *Atlas of U.S. Presidential Elections*.

[26] Specifically, I exclude those reporting Medicaid and Supplemental Security Income receipt.

Distance to Mexico. I measure the great-circle distance from each state's population-weighted centroid to the nearest point on the Mexico land border (state-year invariant).