Trade Effects of Immigration Enforcement: Evidence from U.S. Labor-Intensive Agriculture*

Samyam Shrestha

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Abstract

In recent decades, the farm labor supply in the U.S., which relies heavily on foreign-born workers, has declined, farm labor markets have tightened, and producers have reported labor shortages and rising wages. During this time, U.S. labor-intensive fruit and vegetable (FV) production has reduced, and imports and trade deficits have significantly increased. Connecting these trends, this study examines whether intensified immigration enforcement in the U.S. interior, a supply-side shock to farm labor availability affects domestic and international FV trade flows. First, I demonstrate that a state's FV production decreases with the intensification of immigration enforcement. Using reduced-form gravity models, I then show that immigration enforcement reduces FV exports to other U.S. states and foreign trading partners. I also show that a state's FV imports from other U.S. states increase with enforcement intensity, especially from states with lower enforcement levels. Most of these effects are driven by police-based rather than employment-based enforcement. However, I do not find evidence that immigration enforcement contributes to the rise in international FV imports. These results have important implications for U.S. agricultural and trade policy, food supply systems, and consumer welfare.

Keywords: U.S. farm labor, immigration enforcement, agricultural trade, exports, imports, fruits and vegetables, Poisson Pseudo-Maximum Likelihood

JEL Codes: F16, K37, Q10, Q17

*Samyam Shrestha is a Ph.D. candidate in the Department of Agricultural and Applied Economics at the University of Georgia (samyam@uga.edu). The author thanks Diane Charlton and Nicholas Magnan, whose guidance throughout the project greatly benefited this paper. The author also thanks Mateusz Filipski, Genti Kostandini, and the presentation participants at the UGA Department of Agricultural and Applied Economics and the 2024 AAEA Annual Meeting, New Orleans, for their constructive comments.

1 Introduction

The 2022 U.S. Census of Agriculture reports that the fruit and vegetable (FV) industry generated total sales of USD 43.7 billion, representing 8 percent of total agricultural output and 16.8 percent of crop production nationally (USDA NASS, 2024). However, over the past two decades, U.S. production of major FV crops has declined while imports have grown significantly. Figure 1 illustrates the inflation-adjusted total value of fresh FV imports and exports. Since 1990, the value of U.S. fresh FV imports has increased almost ten-fold, while exports have remained relatively stable. This imbalance has led to a significant increase in the FV trade deficit, growing from less than $1 billion in 1990 to around $20 billion in 2022. Mexico is the U.S.'s largest FV import partner, comprising 58.6 percent of all fresh FV imports in 2022. The U.S. FV trade trends with Mexico show a similar pattern of substantial growth since the 1990s, as Figure 2 shows. According to USDA ERS (2023), the share of imported fresh fruits in the domestic market increased from around 30 percent in 1981 to around 60 percent in 2021, and the share of imported fresh vegetables grew from less than 10 percent in 1981 to almost 40 percent in 2021.

U.S. agriculture relies heavily on foreign-born workers, particularly from rural Mexico, with a significant percentage being undocumented. Foreign-born workers make up approximately 70 percent of the crop production workforce, who work primarily in labor-intensive sectors such as fruits, vegetables, and horticulture (Martin, 2017b). According to the National Agricultural Worker Survey (NAWS) conducted annually by the U.S. Department of Labor (DoL), about 70 percent of these foreign-born workers (or around half of all crop farm workers) are undocumented (Martin, 2017b). Parallel with the shifts in trade dynamics mentioned earlier, the farm labor supply in the U.S. has declined and the farm labor markets have tightened, with farmers reporting labor shortages and rising wages. A growing body of literature has explored the empirical incidence (Richards and Patterson, 1998; Hertz and Zahniser, 2013; Fisher and Knutson, 2013), and examined some of the causes (Kostandini et al., 2014; Fan et al., 2015; Charlton and Taylor, 2016), effects (Kostandini et al., 2014; Rutledge and Mérel, 2023), and potential mitigation strategies (Martin, 2017a; Charlton and Kostandini, 2021) related to the diminishing local availability of agricultural workers in the United States.

This trend coincides with the general decrease in the undocumented population. According to data from the Pew Research Center, the number of undocumented immigrants peaked at around 12.2 million in 2007, which was four percent of the U.S. population, and they accounted for around 5.3 percent of the U.S. labor force. The numbers have since been on a decreasing trend (Krogstad et al., 2017). One widely recognized factor contributing to the decline in the undocumented workforce is the intensified immigration enforcement within the U.S. interior. Research has demonstrated the negative impacts of U.S. interior immigration policies on the undocumented immigrant population in the implementing jurisdictions (Bohn et al., 2014; East et al., 2023). This reduction can be attributed to deportations (East et al., 2023), out-migration to jurisdictions with less stringent enforcement[1] (Bohn et al., 2014; Amuedo-Dorantes et al., 2019), and a decline in migration to areas with stricter enforcement (Smith, 2023). Specifically in agriculture, studies indicate that immigration enforcement reduces the supply of farm labor (Ifft and Jodlowski, 2022) and drives up farm worker wages (Kostandini et al., 2014), thereby increasing production costs.

Combining these three interrelated trends together, this paper explores whether the evolving farm labor dynamics resulting from immigration enforcement contributed to the shifting patterns of trade. Specifically, I investigate the effects of reduced local and seasonal agricultural labor availability induced by immigration enforcement programs on domestic and international trade flows for labor-intensive agricultural commodities, fruits and vegetables. Measuring the effects of local agricultural labor shortages often presents challenges due to the localized, seasonal nature of these shortages and because the reduction in farm worker availability can result from both demand- and supply-side shocks. To address these issues, studies have used policy changes impacting the availability of hired agricultural workers as a supply-side shock to analyze their effects on agricultural outcomes. Following this approach, I exploit the spatial, temporal, and intensity variations in immigration enforcement programs across the contiguous United States to analyze their effects on agricultural trade. I develop a novel measure of state-year enforcement intensity using a weighted share of the state with active immigration enforcement programs in a given year, which I use as the treatment variable.

I first investigate the relationship between immigration enforcement, farm worker expenses, and crop production. Using the Census of Agriculture (CoA) data from the USDA

[1] This is referred to as the 'chilling effect' in the immigration enforcement literature.

National Agricultural Statistics Service (NASS), I show that heightened immigration enforcement reduces the production of fruihts, nuts, and vegetables at the state level. Despite rising labor costs, I find that increased enforcement intensity is associated with lower labor expenses, both in absolute dollar terms and as a share of total operating costs at the state level, likely due to a reduction in the number of farm workers hired. However, I do not find a significant effect of enforcement intensity on total crop production, although FVs account for a sizeable portion of total crop production (almost 17 percent in 2022).

I then begin the trade analysis by focusing on the effects of immigration enforcement on domestic interstate trade flows by employing reduced-form gravity models using the Poisson Pseudo-Maximum Likelihood (PPML) estimator on state-level panel trade flow data from the Freight Analysis Framework (FAF-5). Examining domestic trade patterns provides valuable insights into the factors shaping the U.S. food supply system, particularly for the labor-intensive FV sector. While comparative advantage in agricultural production is often dictated by natural factors such as climate and geography, with regions such as the Sunbelt producing most U.S.-grown fruits and vegetables, state-level regulations and labor policies can also alter these advantages. Changes in immigration enforcement, for instance, can shift the availability of farm labor, leading some states to lose or gain a competitive edge in FV production. Understanding how these policy shifts influence trade between states offers critical insights into the resilience and adaptability of regional food systems.

Results show that immigration enforcement reduces the export of FVs to other U.S. states while increasing domestic imports. Specifically, the increase in imports occurs from U.S. states with below-median maximum enforcement intensity. These effects are not observed for capital-intensive cereal crops. For the international exports analysis, I use USDA ERS state exports based on cash receipts estimates and find that immigration enforcement intensity is negatively associated with international FV exports, driven particularly by reduced fruit exports. Using FAF-5, I find no evidence that higher enforcement intensity is associated with increased FV imports from Mexico and Canada, two major FV import partners for the United States. On the contrary, enforcement intensity is negatively related to imports of both FVs and cereal crops. Consequently, I find no evidence that the significant rise in international FV imports observed empirically is related to changing labor dynamics. Instead, this trend may be explained by factors such as trade agreements and lower production costs in the countries of origin.

Johnson (2014) outlines several factors related to the current competitive market conditions and global trade in FVs, which shape the U.S. FV trade: (1) structural changes in the U.S. food industry, (2) increased competition from low-cost or government-subsidized producers, (3) a relatively open domestic import regime and lower average import tariffs in the U.S. for foreign-produced FVs, (4) non-tariff trade barriers faced by U.S. exports in destination countries, and (5) opportunities for counter-seasonal supplies. In this paper, I specifically focus on the impact of increased production costs resulting from enforcement-induced farm wage increases, thus addressing the structural changes in U.S. agriculture and touching upon the increased competition from low-cost producers.

While increased imports to the U.S. can offer efficiency gains through specialization and comparative advantage, the trade effects of immigration policy remain crucial. U.S. farmers face mixed impacts; some benefit by shifting to more profitable crops, while others may struggle to compete with lower-cost imports, risking job losses and regional economic disruptions. Additionally, strong consumer preferences for locally produced food, driven by concerns over freshness, environmental impact, and support for local economies, may conflict with a purely trade-driven approach. Over-reliance on imports could also expose the U.S. to food security risks, particularly during supply chain disruptions, as seen during the COVID-19 pandemic.

The U.S. has historically expanded the production of labor-intensive FVs by relying on imported labor from Mexico. An alternative to importing cheap labor could be to import cheaper food directly. If U.S. policies increasingly restrict immigration, whether through enforcement or other measures, it is worth investigating whether this might lead to an increase in food imports from countries where labor costs are lower. This potential shift could have significant implications for the U.S. agricultural sector, as it may signal a fundamental structural change in how the U.S. meets its demand for labor-intensive crops. For instance, if the U.S. were to increasingly rely on food imports, this shift might necessitate a reconsideration of how various agricultural programs are structured and funded to align with the new reality where domestic FV production is reduced and imports are further increased.

This paper contributes to several strands of economic literature. First, this study is one of the first to explore the relationship between immigration policy and trade. While existing research has extensively examined the effects of immigration policy on agricultural labor, including labor supply, wages, and farmers' response to such shocks, my work uniquely connects these policies to broader economic implications, focusing on trade patterns, providing new insights into the ripple effects of immigration policy across various economic sectors. To the best of my knowledge, the only previous studies examining the impacts of immigration enforcement on trade are Zahniser et al. (2012) and Devadoss and Luckstead (2011), which use structural models and simulation analysis to find that heightened immigration enforcement reduces international exports.

Second, the study adds to the literature on how policies and regulations can influence competitive advantage among states. There is rich literature exploring the factors determining the competitive advantage between states, identifying factors such as technology and factor endowments (Costinot, 2009), institutions (Svaleryd and Vlachos, 2005; Nunn and Trefler, 2014), market regulations (Costinot, 2009; Santeramo and Lamonaca, 2019), government support programs (Tong et al., 2019), and innovation (Santacreu, 2015). I highlight how labor costs, FV production, and FV prices are interconnected, demonstrating that rising labor costs can make it less efficient for a state to produce FVs, potentially leading to increased imports from other states or countries while decreasing exports.

Third, this study adds to the literature on the factors influencing domestic food supply systems. While environmental factors are crucial in determining regional crop specialization, interstate trade flows are equally important for ensuring a stable and sufficient food supply across the United States. By analyzing the interstate FV movements, I contribute to the limited understanding of how state-level policies impact the domestic food supply. Fourth, this paper is the first to use an aggregate immigration enforcement index that considers multiple state-level policies rather than focusing on a singular policy to analyze the effects of immigration enforcement on agricultural outcomes. While the use of aggregate indices to study the effects of immigration enforcement has become more prevalent, it has not yet been applied to the analysis of agricultural outcomes. By considering the multiplicity of enforcement policies, I address how the combined effects can be greater or qualitatively different from the impact of singular policies.

The remainder of the paper is organized as follows. Section 2 explains the context of this study, relating it to the trends in U.S. agricultural trade, farm labor, and immigration policy. Section 3 describes the theoretical model. Section 4 describes the data and outlines the empirical framework. Section 5 explains the results before Section 6 concludes.

2 Background

This section begins with an overview of U.S. agricultural trade. I then discuss the U.S. agricultural labor market, after which I explain immigration enforcement programs within the U.S. interior and the empirical economic literature on the effects of immigration enforcement on U.S. agriculture.

2.1 U.S. FV Agricultural Trade

The 2022 U.S. Agriculture Census shows that the fruit and vegetable FV industry had total sales of USD 43.7 billion, which accounted for 8 percent of total agricultural output and 16.8 percent of crop production (USDA NASS, 2024). However, over the last two decades, the production of major FV crops in the U.S. has been declining while imports have grown significantly. Agricultural imports from Mexico grew from USD 2.7 billion in 1990 (6.05 billion after adjusting for inflation) to USD 43.4 billion in 2022, around half of which were FVs (U.S. Department of Commerce, 2023). Figure 1 shows the inflation-adjusted total value of imports and exports of fresh fruits and vegetables. The total value of U.S. fresh fruit and vegetable imports has increased around ten-fold since 1990 while the exports have been relatively constant, which has significantly increased the FV trade deficit from less than $1 billion in 1990 to around $20 billion in 2022. According to USDA ERS (2023), the share of imported fresh fruits in the domestic market increased from around 30 percent in 1981 to around 60 percent in 2021, and the share of imported fresh vegetables grew from less than 10 percent in 1981 to almost 40 percent in 2021.

Figure 6 shows the largest import partners for the U.S. in 2022. Mexico is the U.S.'s largest FV import partner, comprising 58.6 percent of all fresh FV imports in 2022, followed by Canada, Peru, Chile, and Guatemala. As shown in Figure 2, the U.S.'s FV trade deficit with Mexico mirrors the total foreign FV trade. Although Canada is a net importer of U.S. FVs, the U.S. FV imports from Canada have been steadily rising since the early 1990s, as shown in Figure 4. In 2022, Canada was the second largest import partner for fresh FVs, covering 8.9 percent of the United States' FV imports. For fresh fruits, export gains were greatest for strawberries/berries, peaches/pears, apples, and grapes. For fresh vegetables, export gains were greatest for lettuce, spinach, tomatoes, potatoes, and legumes/beans (Johnson, 2014). For processed products, export gains were for processed potato products, certain preserved vegetables, and fruit juices and juice mixtures. Contrarily, increased imports were greatest for fresh citrus, strawberries/berries, tropical fruits (excluding bananas), grapes, peaches/pears, plums/apricots, and apples. Imports of preserved mushrooms and processed tomatoes declined over time (Johnson, 2014).

Johnson (2014) highlights five major factors contributing to the changing international trade dynamics for U.S. produced FVs: (1) market factors like exchange rate fluctuations and structural changes in the U.S. food industry, (2) increased competition from low-cost or government-subsidized production elsewhere, (3) relatively open domestic import regime and lower average import tariffs in the U.S. for foreign-produced FVs along with trade preferences under free trade agreements, (4) continued non-tariff trade barries to U.S. exports in some countries like import and inspection requirements, technical product standards, and sanitary and phytosanitary requirements, and (5) opportunities for counter-seasonal supplies, driven in part by increased domestic and year-round demand for FVs.

This paper specifically focuses on the first two factors: the structural changes in agricultural labor markets and the subsequent price increase due to the rise in production costs that affects the competitive advantage of U.S. states in producing FVs on the face of low-cost, government-subsidized production elsewhere. Compared to other countries, U.S. production costs are relatively high and generally increasing due to rising costs for farm inputs, including labor expenses. Most fruits and vegetables are fragile and perishable and must be hand-picked, limiting opportunities for mechanized harvesting. This makes FV production very labor-intensive. Farm labor accounts for 42 percent of the variable production expenses for U.S. FVs (Martin and Calvin, 2011). An increase in production costs due to increased labor expenses could have direct effects on the production of FVs and can have spillovers on the U.S.'s competitive advantage in the international markets.

2.2 U.S. Farm Labor

The U.S. agriculture relies heavily on foreign-born workers, especially from rural Mexico, a significant percentage of whom are undocumented in the U.S. Foreign-born workers comprise approximately 70 percent of the crop production workforce (Martin, 2017b), particularly as hired workers for labor-intensive crops like FVs and horticulture. According to the National Agricultural Worker Survey (NAWS) conducted annually by the U.S. Department of Labor (DoL), about 70 percent of these foreign-born workers (or around half of all crop farm workers) are undocumented (Martin, 2017b). This dependence on foreign workers is rooted in the labor-intensive nature of these industries, where tasks such as planting, tending, harvesting, and processing for crop production require substantial manual labor. Workers from rural Mexico, with experience in agriculture and willingness to undertake physically demanding roles, fill the gap in the labor market that domestic workers are often unwilling or unable to fill.

The history of hiring foreign workers in the U.S. agriculture sector goes back to the Bracero Program during the Second World War, conceived to fill labor shortages in the agricultural industry as U.S. workers were drawn into the military (Clemens et al., 2018). The program allowed millions of Mexican men to work on temporary labor contracts in the U.S., primarily in agriculture. Mexican farm workers continued to fill the role of producing labor-intensive food products in the mid-1900s, as U.S. labor continued to shift away from farms to other sectors. An elastic labor supply from rural Mexico enabled the FVH production to expand despite the withdrawal of U.S.-born workers from the farms. This elastic labor supply also discouraged labor-saving technological change and created challenges for organizing farm labor (Martin and Taylor, 1998; Martin, 2003).

In recent decades, there has been a sharp decline in the supply of Mexican seasonal farm workers in the U.S. Since 1980, the share of rural Mexicans working in agriculture has declined by roughly 1 percent per year (Charlton and Taylor, 2016). Growing literature explores the causes (Charlton and Taylor, 2016), effects (Rutledge and Mérel, 2023), and potential mitigation strategies (Martin, 2017a; Charlton and Kostandini, 2021) related to seasonal farm labor shortage in the U.S. This reduction can be driven by a multitude of factors such as the implementation of more stringent border and immigration enforcement policies in the U.S. (Luo et al., 2023; Luo and Kostandini, 2022; Kostandini et al., 2014), disproportional increase in the demand and wages for non-agricultural sector labor within local economies in the U.S. (Castillo and Charlton, 2023), the increase in education and income levels for Mexicans and their departure from agriculture (Charlton and Taylor, 2020), and the increased competition from Mexican farms for Mexican labor (Zahniser et al., 2018), among others. Furthermore, the reduced mobility of aging foreign-born seasonal farm workers within the U.S. has aggravated seasonal farm labor shortages (Fan et al., 2015; Arteaga and Shenoy, 2023). There is evidence that these factors have affected FV production (Rutledge and Mérel, 2023).

The removal of all undocumented immigrants from U.S. agriculture would have a significant impact on crop production and agricultural GDP. Richards (2018) shows that the removal of 50 percent of undocumented farm workers in California would lead to a 22 percent increase in farm worker wages. Zahniser et al. (2012) uses a computable general equilibrium (CGE) model to evaluate the potential effects of a reduction in undocumented farm workers due to tightened immigration enforcement. The study shows that an immigration enforcement policy that removes 5.8 million people over 15 years causes a 2-4 percent decrease in output for labor-intensive agricultural sectors and reduces agricultural exports by 0.8-6.3 percent. A 2017 industry report estimated that without undocumented farm workers, New York's agricultural output would decrease at least 24 percent (more than $1.37 billion) and an estimated 23,490 jobs would be lost, including jobs held by U.S. citizens (Farm Credit East, 2017). This reduction occurs because many U.S. citizen jobs depend on maintaining full production capacity, and when farms cannot operate efficiently without undocumented workers, it triggers job losses throughout the agricultural supply chain, from processing to distribution.

2.3 Immigration Enforcement Programs in the U.S. Interior

The Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA) brought major immigration policy changes in the U.S., which was intensified after the September 11 attacks in 2001. By 2005, most immigration policies were starting to be adopted at various jurisdiction levels. In general, there are two broad types of immigration enforcement programs: police-based measures that involve the local or state police and employment-based measures that involve the employers.

Police-based measures usually involve agreements between the Director of the Immigration and Customs Enforcement Agency (ICE) and the state and local (county or city level) law enforcement agencies. ICE trains local law enforcement agencies to identify and arrest undocumented immigrants. The Immigration and Nationality Act 287g and Secure Communities are police-based measures. Contrarily, employment-based measures require employers by law to verify the work eligibility of prospective hires. E-Verify is the most notable type of employer-based immigration enforcement policy. I focus on four different types of immigration enforcement policies highlighted below.

Immigration and Nationality Act 287(g): The Immigration and Nationality Act Section 287(g) is a provision that allows the Department of Homeland Security (DHS) to enter into agreements with state and local law enforcement agencies, permitting designated officers to perform immigration law enforcement functions. Under this program, officers receive training and authorization to identify, process, and unlawfully detain individuals in the United States. The goal of 287(g) is to enhance the collaboration between federal immigration authorities and local law enforcement to improve the identification and removal of criminal aliens. The implementing jurisdictions adopted the policy between 2002 and 2010. Figure 11 shows the variation in the implementation of county-level 287(g) program throughout U.S. counties.

Secure Communities: Secure Communities is a DHS program designed to identify and remove undocumented immigrants with criminal records. The program operates by sharing fingerprints taken by local law enforcement agencies during bookings with federal immigration databases. If a match is found, Immigration and Customs Enforcement (ICE) is notified to take appropriate action. The program was rolled out county by county between 2008 and 2013 and was ultimately adopted by all U.S. counties. Figure 12 illustrates the variation in the adoption of Secure Communities program at the county level.

E-Verify: E-Verify is an internet-based system that allows employers to verify the employment eligibility of their employees. Managed by the U.S. Citizenship and Immigration Services (USCIS) in partnership with the Social Security Administration (SSA), E-Verify compares information from an employee's Form I-9 to data from the SSA and DHS records to confirm their eligibility to work in the United States. The policy was implemented at the state level starting in 2004 and was adopted by several states by 2015.

Omnibus Bill: Omnibus Immigration Laws include three or more immigration-related laws in a single bill and aim to construct immigration enforcement regimes that could affect undocumented immigrants in many respects, including "show me your papers" laws, public benefit bans limiting undocumented immigrants' access to health benefits, public education benefits, and driver's licenses. Most of the implementing jurisdictions adopted the policies between 2006 and 2014.

2.4 Effects of Immigration Enforcement on U.S. Agriculture

There is a rapidly growing literature on the effects of immigration enforcement on outcomes as diverse as the population of likely undocumented immigrants in the implementing jurisdictions (Bohn et al., 2014; Orrenius and Zavodny, 2016), labor market outcomes for both undocumented immigrants and U.S. citizens (East et al., 2023; East and Velásquez, 2022), education (Amuedo-Dorantes and Lopez, 2017a), child welfare (Amuedo-Dorantes et al., 2018; Amuedo-Dorantes and Arenas-Arroyo, 2019; Amuedo-Dorantes et al., 2015, 2022; Amuedo-Dorantes and Puttitanun, 2018), self-employment (Amuedo-Dorantes et al., 2022), marriage and fertility (Amuedo-Dorantes et al., 2020), mental health (Luo and Kostandini, 2023), and political participation (Amuedo-Dorantes and Lopez, 2017b).

There is a growing literature on the effects of immigration enforcement on U.S. agriculture. Evidence shows that such restrictive policies affect the supply of farm workers and farm worker wages. Farm labor supply (Ifft and Jodlowski, 2022; Luo and Kostandini, 2022; Luo et al., 2023), which subsequently affect various outcomes like output choices (Kostandini et al., 2014; Cruz et al., 2022), farm profitability (Kostandini et al., 2014), the number of agricultural establishments in operation (Charlton and Kostandini, 2021), agricultural production (Rutledge and Mérel, 2023), and total acres of operated farmland (Luo and Kostandini, 2022). There is also evidence that such policies increased labor-saving technologies among farmers (Charlton and Kostandini, 2021). Nonetheless, there is evidence that such policies do not affect wages mostly because farms switched away from labor-intensive to capital-intensive crop production (Luo and Kostandini, 2022).

There are two gaps in the literature on the effects of immigration enforcement policies on agricultural outcomes. First, most of these studies focus on a singular enforcement policy by controlling for the adoption of other policies. The combined impact of multiple policies can differ significantly from individual policies, as their interactions may produce compounding effects greater or different than the sum of each policy's impact. Second, if immigration enforcement reduces the production of labor-intensive crops as shown by the literature, the trade of such crops should reduce as well. So far, there has only been some indicative findings on this topic using structural models (Devadoss and Luckstead, 2011; Zahniser et al., 2012). This paper is a first attempt to use reduced-form methods to establish the relationship between immigration enforcement and the trade of labor-intensive agricultural commodities at both the interstate and international levels.

3 Theoretical Framework

To investigate the effects of immigration policy on trade, I start with the canonical gravity model by Anderson and Van Wincoop (2003) and incorporate the enforcement variable. I follow two crucial assumptions of the model. First, all goods are differentiated by place of origin and each region specializes in the production of only one good. Although Anderson and Van Wincoop (2003) assumes that the supply of each good is fixed, I relax this assumption due to changes in supply dictated by the decrease in production. As I will discuss later, I treat supply as endogenous to the model, depending on immigration enforcement. Second, I assume that preferences are homothetic and are approximated by a Constant Elasticity of Substitution (CES) utility function.[2] I begin with preferences for consumers in region j who maximize the following utility function:

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

where c_{ij} is the consumption of goods from region i by consumers in region j, α_i is a positive distribution parameter, and σ is the elasticity of substitution between goods.

Consumers maximize their utility subject to the budget constraint:

$$\sum_i p_{ij} \cdot c_{ij} = y_j \tag{2}$$

where p_{ij} is the price of goods from region i in region j, and y_j is the nominal income of region j.

The demand function for goods from region i by consumers in region j is derived by maximizing utility (1) subject to the budget constraint (2):

$$c_{ij} = \alpha_i \cdot \left(\frac{p_{ij}}{P_j} \right)^{-\sigma} \cdot \frac{y_j}{p_{ij}} \tag{3}$$

[2]The CES utility function offers specific properties that make it particularly useful in modeling trade and other economic environments where consumers or firms face choices among differentiated goods from multiple sources. Below are the main benefits and reasons for using the CES utility function: It allows for straightforward representation of goods as differentiated by their place of origin, it assumes a constant elasticity of substitution between any two goods, which simplifies the analysis as it implies that the substitution patterns between goods and consistent, it provides a convenient way to aggregate the prices of different goods into a single price index called the CES price index, and it assumes homothetic preferences, which allows for more superficial analysis across various income levels and regions.

where P_j is the CES price index in region j, given by:

$$P_j = \left(\sum_i \alpha_i \cdot p_{ij}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{4}$$

The price index P_j reflects the cost of living in region j, capturing the prices of goods imported from all regions i.

The price p_{ij} that consumers in region j face for goods from region i is not just the supply price P_i from region i but also includes trade costs τ_{ij}, which drive a wedge between the price at which the producer sells goods and the price paid by the consumer. Thus, I express the price p_{ij} as:

$$p_{ij} = P_i \cdot \tau_{ij} \tag{5}$$

where P_i is the supply price in region i, and τ_{ij} is the trade cost factor between regions i and j. Trade costs include all costs incurred in getting the goods from the exporter to the importer, such as transportation costs, tariffs, and other barriers.

I introduce the immigration enforcement variable μ_i, which affects the production costs in region i by reducing the availability of farm workers and creating local labor shortages. As enforcement intensity increases, production costs rise, leading to an increase in the supply price P_i. I can model this impact by adjusting the supply price as:

$$P_i' = P_i \cdot (1 + \gamma \mu_i) \tag{6}$$

where μ_i is the immigration enforcement intensity such that $0 \leq \mu_i \leq 1$, where 0 denotes no enforcement, and 1 denotes highest possible enforcement, and $\gamma \geq 0$ is a parameter that measures the sensitivity of the supply price to changes in enforcement intensity. Practically, γ should vary at the crop level, such that for labor-intensive agricultural products, the value of γ is higher, but since I assume that a region specializes in the production of only one good, this property can be relaxed.

Substituting this adjusted supply price into the price equation, the price faced by consumers in region j becomes:

$$p_{ij} = P_i \cdot (1 + \gamma \mu_i) \cdot \tau_{ij} \tag{7}$$

Substituting equation (7) into the demand function (3), I get the nominal value of exports from region i to region j:

$$x_{ij} = p_{ij} \cdot c_{ij} = \alpha_i \cdot \left(\frac{P_i \cdot (1 + \gamma\mu_i) \cdot \tau_{ij}}{P_j} \right)^{1-\sigma} \cdot y_j \tag{8}$$

To ensure market clearance, the income in region i must equal the sum of its exports to all regions:

$$y_i = \sum_j x_{ij} = \sum_j \alpha_i \cdot \left(\frac{P_i \cdot (1 + \gamma\mu_i) \cdot \tau_{ij}}{P_j} \right)^{1-\sigma} \cdot y_j \tag{9}$$

Using the market-clearing condition (9), I can solve for the scaled prices α_i. To do this, I assume that all regions i are symmetric, meaning that trade costs τ_{ij} are the same in both directions (i.e., $\tau_{ij} = t_{ji}$) and that preferences and production structures are also symmetric. The price index P_j is then given by:

$$P_j^{1-\sigma} = \sum_i (\alpha_i \cdot P_i \cdot (1 + \gamma\mu_i) \cdot \tau_{ij})^{1-\sigma} \tag{10}$$

Now, I introduce the concept of multilateral resistance, as detailed by Anderson and Van Wincoop (2003). The multilateral resistance terms Π_i and P_j account for the fact that trade costs are relative to the overall resistance faced by each trading partner. The multilateral resistance for the exporter is given by:

$$\Pi_i = \left(\sum_j \left(\frac{\tau_{ij}}{P_j} \right)^{1-\sigma} \cdot \theta_j \right)^{\frac{1}{1-\sigma}} \tag{11}$$

where θ_j is the income share of region j, defined as $\theta_j = \frac{y_j}{y_W}$, with y_W being the world income $y_W = \sum_j y_j$.

Similarly, the multilateral resistance for the importer j is:

$$P_j = \left(\sum_i \left(\tau_{ij} \cdot \frac{\Pi_i}{(1 + \gamma\mu_i)} \right)^{1-\sigma} \cdot \theta_i \right)^{\frac{1}{1-\sigma}} \tag{12}$$

These expressions, equations (11) and (12), account for the relative difficulty of trading between regions considering all potential trading partners.

Substituting these multilateral resistance terms back into the original demand equation, the gravity equation is derived as follows:

$$x_{ij} = \frac{y_i \cdot y_j}{y_W} \cdot \left(\frac{\tau_{ij}}{\Pi_i \cdot (1 + \gamma \mu_i) \cdot P_j} \right)^{1-\sigma} \tag{13}$$

This equation shows that the value of exports x_{ij} between regions i and j depends on the product of their incomes y_i and y_j, scaled by world income y_W, and is inversely related to the product of their multilateral resistance indices Π_i and P_j as well as the trade cost τ_{ij}. The introduction of the immigration enforcement variable μ_i increases the supply price P_i and therefore reduces the trade flow x_{ij}.

Finally, I analyze the effect of immigration enforcement intensity on trade flows by taking the partial derivative of x_{ij} with respect to μ_i:

$$\frac{\partial x_{ij}}{\partial \mu_i} = \frac{\partial}{\partial \mu_i} \left[\frac{y_i \cdot y_j}{y_W} \cdot \left(\frac{\tau_{ij}}{\Pi_i \cdot (1 + \gamma \mu_i) \cdot P_j} \right)^{1-\sigma} \right] \tag{14}$$

Since the term $\frac{y_i \cdot y_j}{y_W}$ is independent of μ_i, the derivative simplifies to:

$$\frac{\partial x_{ij}}{\partial \mu_i} = \frac{y_i \cdot y_j}{y_W} \cdot (1 - \sigma) \cdot \left(\frac{\tau_{ij}}{\Pi_i \cdot (1 + \gamma \mu_i) \cdot P_j} \right)^{1-\sigma} \cdot \frac{\partial}{\partial \mu_i} \left[\frac{1}{(1 + \gamma \mu_i)} \right] \tag{15}$$

Taking the derivative of the term $\frac{1}{(1+\gamma\mu_i)}$ with respect to μ_i, I obtain:

$$\frac{\partial}{\partial \mu_i} \left[\frac{1}{(1 + \gamma \mu_i)} \right] = \frac{-\gamma}{(1 + \gamma \mu_i)^2} \tag{16}$$

Substituting this into the previous expression, I get:

$$\frac{\partial x_{ij}}{\partial \mu_i} = \frac{y_i \cdot y_j}{y_W} \cdot (1 - \sigma) \cdot \left(\frac{\tau_{ij}}{\Pi_i \cdot (1 + \gamma \mu_i) \cdot P_j} \right)^{1-\sigma} \cdot \frac{-\gamma}{(1 + \gamma \mu_i)^2} \tag{17}$$

Simplifying further, I can write:

$$\frac{\partial x_{ij}}{\partial \mu_i} = -\gamma \cdot \frac{y_i \cdot y_j}{y_W} \cdot (1 - \sigma) \cdot \left(\frac{\tau_{ij}}{\Pi_i \cdot (1 + \gamma \mu_i) \cdot P_j} \right)^{1-\sigma} \cdot \frac{1}{(1 + \gamma \mu_i)^2} \tag{18}$$

The negative sign in the expression for $\frac{\partial x_{ij}}{\partial \mu_i}$ indicates that as the immigration enforcement intensity μ_i increases, the trade flow x_{ij} decreases. This decrease in exports occurs because higher enforcement leads to an increase in the supply price P_i, which, when passed through the trade cost τ_{ij}, results in a higher price faced by the importer j. Consequently, the demand for goods from region i declines, reducing the overall export volume x_{ij}.

The magnitude of the impact depends on several factors. First, the parameter γ, which measures the sensitivity of the supply price to enforcement, plays a critical role. A larger γ implies that the supply price P_i is more responsive to changes in μ_i, leading to a greater reduction in trade flow as enforcement intensifies. Second, the elasticity of substitution σ also influences the outcome. A higher σ suggests that goods are more easily substitutable, which exacerbates the decline in exports when prices rise. Finally, the level of enforcement μ_i itself affects the degree of change, with higher levels of enforcement leading to more significant reductions in trade.

When demand is elastic ($\sigma > 1$), goods from different regions are easily substitutable. An increase in μ_i raises the supply price P_i significantly, leading to a substantial increase in the price p_{ij} faced by the importer. Consumers in region j will sharply reduce their demand for goods from region i, switching to cheaper alternatives. As a result, the trade flow x_{ij} decreases significantly. However, when demand is inelastic ($\sigma < 1$), goods from different regions are not easily substitutable. Even if μ_i increases, leading to a higher supply price P_i, the reduction in demand for goods from region i is less pronounced. Consumers may continue purchasing goods from region i despite the higher prices, leading to a smaller decrease or even an increase in total import expenditure.

The comparative statics analysis, therefore, shows that the trade flow x_{ij} is negatively affected by increases in immigration enforcement intensity μ_i. However, the extent of this reduction depends on the elasticity of substitution σ. If demand is elastic, the reduction in trade flows is more significant, as consumers shift to alternative sources. If demand is inelastic, the reduction is less severe, and overall import expenditure may not decrease substantially.

As discussed earlier, immigration enforcement in region i raises production costs, particularly for labor-intensive goods. This increase in production costs leads to an increase in the local supply price P_i, making goods produced in region i more expensive. As a result, consumers in region i may shift their demand towards goods from other regions, such as region j, where prices remain lower or have risen less sharply.

As for imports, as the price of goods from region i increases, imports from region j become relatively more attractive. This substitution effect is particularly pronounced when the elasticity of substitution σ is large, meaning that consumers can easily switch from local goods to imports.

The gravity equation for exports from region j to region i (i.e., imports into region i) is given by:

$$x_{ji} = \frac{y_j \cdot y_i}{y_W} \cdot \left(\frac{t_{ji}}{\Pi_j \cdot (P_i \cdot (1 + \gamma\mu_i))} \right)^{1-\sigma} \tag{19}$$

The key term in this equation is $P_i \cdot (1 + \gamma\mu_i)$, which captures the price increase in region i due to immigration enforcement intensity μ_i. As this term increases, imports from region j become relatively cheaper, leading to a reallocation of trade flows towards region j.

To quantify this effect, the comparative statics derived earlier show that as μ_i increases, the imports from region j rise due to the increased relative price of local goods in region i. While the formal derivation has been shown in the export analysis, the key takeaway here is that higher immigration enforcement in region i leads to higher imports from region j as consumers in region i seek cheaper alternatives to the more expensive locally produced goods. Therefore, the increase in immigration enforcement intensity μ_i causes a shift in consumption patterns in region i, driving up imports from region j as consumers substitute away from more expensive local goods toward cheaper imported goods.

4 Data and Empirical Methods

4.1 Measuring Immigration Enforcement Intensity

I assemble the data on the implementation of immigration enforcement policies from several sources. I obtained the data on the year of SC implementation at the county level from East et al. (2023), the data on the E-Verify implementation at the state level from Luo and Kostandini (2023) and Orrenius and Zavodny (2015), the data on the Omnibus Immigration Bill implementation at the state level from Luo and Kostandini (2023), and the data on the Immigration and Nationality Act 287(g) implementation at the county and state levels from Kostandini et al. (2014). I limit the sample until 2012 due to the change in scope for two policies. 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.

I create the treatment variable denoting the state-level immigration enforcement intensity, ENF_{it}, using equation (20), 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[3] 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.[4] 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 calculate the weighted share for five immigration policies: the E-Verify, the Immigration and National Act 287g agreements at the state and county levels, the Secure Communities program, and the Omnibus Bill:

$$ENF^k_{it} = \frac{1}{A_{i,1997}} \sum_{c \in i} \frac{1}{12} \sum_{m=1}^{12} \mathbb{1}(E^k_{mc}) A_{c,1997} \tag{20}$$

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 (20).

$$ENF_{it} = \sum_{k \in K} ENF^k_{it} \tag{21}$$

Figure 9 shows the average enforcement intensity for 50 U.S. states from 2001-14 using this index. Figure 10 shows the spatiotemporal variation in the immigration enforcement

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

[4]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 agrarian 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.

intensity over time. For a better interpretation of coefficients, I also use the normalized version of this index. While many papers have used this method in general economics, most previous reduced-form papers analyzing the effects of immigration enforcement on agricultural outcomes focus on the effects of a singular policy at a time. The aggregate effects of multiple policies implemented simultaneously could differ significantly from the effects of individual enforcement policies because the interaction of multiple policies can create compounding effects, where the combined impact is greater or different than that of a singular policy.

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.

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 jurisdiction, and, consequently, this reduction decreases the production of labor-intensive commodities such as fruits and vegetables, which may affect their consumption and trade. 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 (22).

$$y_{it} = \Omega_i + \Lambda_t + \alpha ENF_{it} + X_{it}'\beta + \varepsilon_{it} \tag{22}$$

In the equation, y_{it} is the outcome variable in the state, i, and year, t. I look at the effects on four outcomes: (1) total labor expenses (hired and contract) as a percentage of the total operating costs, (2) total agricultural labor expenses (hired and contract), (3) total crop production, and (4) total production 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 controls, including the Bartik-style control and weather variables. I include the Bartik-style measure of labor demand as a control (Bartik, 1992). The variable is equal to $\sum_k (s_{ik0} \times g_{kt})$, where s_{ik0} is the share of 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 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). I add this term in the regression to account for changes in economic conditions that might affect the volume of labor-intensive agricultural commodity production. As the sample period spans the Great Recession, Bartik-style control helps to isolate the effects of the local economic shocks arising from the recession. As the Bartik measure 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.[5]

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.[6] Regarded as

[5]While traditionally, the Bartik measure is used as an instrument, several recent papers like East et al. (2023) use it as a regression control variable.

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

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 Greenstone, 2007). PRISM generates precipitation and temperature at 4×4 kilometer grid cells for the entire U.S. For precipitation, PRISM considers the orographic effect, where mountains influence precipitation patterns, by modeling how air masses interact with terrain, and 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. Finally, ε_{it} is the idiosyncratic standard errors clustered at the state level.

4.3 Effects on Exports

For the trade analysis (except for international exports), 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 (BTS) and the Federal Highway Administration (FHWA). 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.[7] 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,[8] which are often the most impacted crop types due to local, seasonal labor shortages. I also use the SCTG product code of “02,” which includes cereal crops for placebo 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.

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. I use the FAF-5 data for the domestic trade and international import (not export) analysis. For the domestic trade flows, FAF-5

[7]Except, as I note later, Mexico and Canada.

[8]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

measures the trade flow between each state.

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 (23), which is loosely derived from the structural gravity model by Anderson and Van Wincoop (2003) and is similar in spirit to Tong et al. (2019). PPML is suited for the case for two crucial reasons. As Silva and Tenreyro (2006) notes, first, it addresses the issue of inconsistency in the gravity estimates due to heteroskedasticity; and second, the multiplicative property of the gravity model allows the estimator to account for observations with zero trade flows (Shepherd et al., 2013), which is probable in many cases as not all states trade products with all other states or foreign trading partners (Haveman and Hummels, 2004).

$$EX_{ijt} = exp\Big[\Gamma_{jt} + \Psi_{ij} + \alpha_1 ENF_{it} + X'_{it}\beta + \varepsilon_{ijt}\Big] \tag{23}$$

In the equation, i, j, and t index exporter, importer, and year respectively. EX_{ijt} is the volume of labor-intensive agricultural commodities exported from U.S. state i to state or country j in year t.[9] 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).[10] Several other factors like the importer's GDP (Anderson and Van Wincoop, 2003), currency exchange rate volatility (for international trade) (Bacchetta and Van Wincoop, 2000; Auboin and Ruta, 2013), between states 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 country, 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,

[9]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.

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

and assuming that the importer-level policies do not vary between U.S. states,[11] that should not bias the estimates.[12] 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 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 countries, the canonical 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 (22), I use the Bartik-style control and weighted state-level temperature and precipitation measures as control variables.

One crucial limitation of the FAF-5 data is that the SCTG product code of "03" includes soybeans, which is a major capital-intensive crop in the Midwest. To deal with this issue, I control for the state-level soybean production in the regressions. Furthermore, although this is a limitation that should potentially bias the coefficients towards zero, as I will dis-

[11]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.

[12]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.

cuss in the results section, the coefficients are still statistically and economically significant, although they may have a downward bias.

The term ε_{ijt} is the idiosyncratic standard error clustered at the origin-by-destination level. I weigh observations in the inter-state trade regressions using the natural log of the product of agricultural GDPs for states i and j divided by the distance between the centroids of the two states ($\frac{GDP_i \times GDP_j}{Dis\tau_{ij}}$). 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 5.6, I address and refute any endogeneity concerns related to ENF_{it}.

4.3.1 Effects on International Exports

For the international export analysis, I use the state agricultural trade data compiled by the USDA Economic Research Services (ERS) from the U.S. Department of Commerce and the Bureau of Census. I use the state exports using cash receipts estimates that capture the value of the state's agricultural production that is exported. USDA, ERS estimates calendar-year state exports of total and selected commodities based on U.S. farm cash receipts data starting in 2000. All export values are calibrated so the sum of state export estimates for a commodity equals the total U.S. export value for that commodity. I use the values for fresh fruits and fresh vegetables for the main export analysis and the values of corn and soybean for placebo tests. I use this data instead of the FAF-5 export data because of two benefits: first, the categorization of commodities is better with the USDA dataset, and it includes annual data since 2000. I use years 2000-12 for the analysis. I use the PPML gravity specification in equation (24).

$$EX_{ijt} = exp\Big[\Theta_i + \Lambda_t + \alpha_1 ENF_{it} + X'_{it}\beta + \varepsilon_{ijt}\Big] \tag{24}$$

where Θ_i is the exporter fixed effects, Λ_t is the year fixed effects. The error term, ε_{ijt}, is clustered at the exporter level. One limitation of the data is that it only provides an aggregate export value at the state-year level. I use several properties of the data and the setting to posit two facts that allow us to use these fixed effects in a one-sided (exporter-sided; without importer information) to provide valuable information on the effects of state-level enforcement on international exports.

First, all trade-restricting policies of the importer (that I control using the importer-year fixed effects, Γ_{jit}, in equation (23)) are constant throughout the U.S. states, such as tariffs or sanctions imposed by importer countries, and the currency exchange rates. This assumption allows us to use the year fixed effects to absorb these year-specific unobservables. Second, the exporter-importer level time-invariant characteristics, such as distance to the nearest port and whether they share a border (that I control using the importer-exporter dyadic pair fixed effects, Γ_{jit}, in equation (23)), are absorbed by the state fixed effects.

4.4 Effects on Imports

To analyze the effects of immigration enforcement intensity on imports, I estimate equation (25), which is identical to equation (23) that I use for the export analysis, except for a few adjustments. While i and j still denote the exporter and importer states, I replace origin-level enforcement index and controls with destination-level enforcement index, ENF_{jt}, and controls, and switch the destination-by-year fixed effects with origin-by-year fixed effects, Γ_{it}, to control for time-varying importer-specific trade-promoting and trade-restricting components, as well as the bilateral trade costs and factors determining the exporter's easy of market access.

$$EX_{ijt} = exp\Big[\Gamma_{it} + \Psi_{ij} + \alpha_1 ENF_{jt} + X'_{jt}\beta + \varepsilon_{ijt}\Big] \tag{25}$$

I still retain EX_{ijt} as the outcome variable as the value denotes the exports from state i to state j, but now, 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.

As stated above, I use the FAF-5 data for both interstate and international imports. For international imports, I only use the data for imports from Mexico and Canada (separately) for two reasons. First, the FAF-5 data provides U.S.-state-to-continent import and export data, except for Mexico and Canada. Second, Mexico and Canada are the largest import partners of the U.S., comprising 58.5 percent and 8.9 percent of FV imports, respectively. Figures 1 and 2 also show that the rise in U.S. FV imports is primarily driven by increased FV imports from Mexico.

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 drive the trade dynamics. Table 1 shows the effects of immigration enforcement on farm labor expenses and crop production using equation (22) and the state-level USDA NASS Census of Agriculture data from 1997, 2002, 2007, and 2012. I look at four outcome variables: (1) total labor expenses (hired and contract) as a percentage of the total operating costs, (2) total agricultural labor expenses (hired and contract), (3) total crop production, and (4) total production of fruits, nuts, and vegetables.

Results in columns (1) and (2) from panel B show that a one standard deviation increase in immigration enforcement intensity (which is equal to the average immigration enforcement in 2012) leads to a 2.6 percent decrease in the total labor expenditure as a percentage of the total operating costs and a 7.6 percent decrease in total agricultural labor expenses, respectively. Coefficients from regressions using a non-normalized index are comparable to those using normalized treatment, although they are slightly lower in magnitude. Despite the potential rising labor costs due to the reduced availability of farm workers due to immigration enforcement as documented by previous literature (Kostandini et al., 2014), this effect is likely due to a reduction in the number of farm workers hired. These findings are parallel to those from Charlton et al. (2023).

Column (3) shows that a one standard deviation increase in immigration enforcement intensity has a 0.80 percentage point decrease in the total crop production, but which is not statistically significant. Similarly, column (4) shows that a one standard deviation increase in the intensity decreases the production of fruits, nuts, and vegetables by 6.9 percent, statistically significant at the 1 percent level. There is some empirical evidence that farmers switch from producing labor-intensive to capital-intensive agricultural products following the implementation of immigration enforcement (Cruz et al., 2022). Therefore, although FVs account for a sizeable portion of total crop production (almost 17 percent in 2022), switching from labor-intensive to capital-intensive crops might have offset the production effects when considering crop output.

5.2 Effects on Domestic Trade Flows

I start by discussing the effects on domestic trade flows before examining the effects on international trade. Table 2 shows the effects of immigration enforcement on interstate export of fruits and vegetables. All regressions use the reduced-form gravity model with Poisson Pseudo-Maximum Likelihood (PPML) estimator illustrated in equation (23) and the FAF-5 dataset from 1997, 2002, 2007, and 2012. I show results using trade flows using monetary value (in terms of million U.S. dollars adjusted for inflation to the 2012 value) and weight (thousand tons). I show results from regressions with and without state-level control variables.

Panel B, Column (2), which uses my preferred model with importer-exporter pair fixed effects and state controls, shows that a one standard deviation increase in enforcement intensity is associated with a 13.14 percent $((\exp(-0.141)-1)\times 100)$ decrease in the outflow of FVs to other U.S. states in terms of monetary value. The results are the same in terms of weight. Column (4) shows that a one standard deviation increase in enforcement intensity is associated with a -14.09 percent $((\exp(-0.152) - 1) \times 100)$ decrease in FV exports to other U.S. states. The estimates using the non-normalized index in panel B are similar in magnitude and direction, although higher in magnitude, a pattern identical to table 1.

Table 3 uses equation (25) to analyze the effects of enforcement intensity on FV import from other U.S. states. Columns (2) and (4) show the results from my preferred specification with importer-exporter pair fixed effects, exporter-by-year fixed effects, and state-level controls. Column (2) shows that a one standard deviation increase in enforcement intensity is associated with a 13.44 percent $((\exp(0.126) - 1) \times 100)$ increase in FV trade flow inward from other U.S. states in terms of monetary value, which is statistically significant. Similarly, column (4) shows that a one standard deviation increase in enforcement intensity leads to a 15.40 $((\exp(0.143) - 1) \times 100)$ percent increase in interstate FV imports.

These results indicate that immigration enforcement reduces the outflow of FVs to other U.S. states and increases the inflows.

5.2.1 Accounting for Trade Partner's Enforcement Intensity

If immigration enforcement intensity decreases the flow of FVs 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 (23) considers the immigration enforcement intensity at the origin state but not the intensity at the destination state, which is controlled for by the destination-by-year fixed effects, Γ_{jt}. Holding the origin state immigration enforcement intensity constant, the enforcement intensity at the destination may also affect the volume and magnitude of interstate trade. If the destination state experiences a decline in domestic production of fruits and vegetables, it should increase the trade demand to reduce local shortage. I thus check whether there are any differential effects on trade based on the destination state enforcement intensity by incorporating an interaction term between ENF_{it} and the binary variable called $HIGH_j$ that takes the value of 1 if the enforcement intensity is greater than the median enforcement intensity in the destination state, and zero otherwise.[13,14] Equations (26) illustrate this specification. In the equation, the dyadic pair fixed effects term, Ψ_{ij}, absorbs the stand-alone $HIGH_j$ term. I also estimate the import equivalent of equation (26) to explore whether the heterogeneity in origin enforcement intensity affects imports. Equation (27) shows this specification. Equation (27) is the equivalent for the importer analysis where $HIGH_i$ is a binary variable that equals one if the enforcement intensity is greater than the median enforcement intensity in the origin state, and zero otherwise.

$$EX_{ijt} = exp\Big[\Gamma_{jt} + \Psi_{ij} + \alpha_1 ENF_{it} + \alpha_2 ENF_{it} \times HIGH_j + X'_{it}\beta + \varepsilon_{ijt}\Big] \tag{26}$$

$$EX_{ijt} = exp\Big[\Gamma_{it} + \Psi_{ij} + \alpha_1 ENF_{jt} + \alpha_2 ENF_{jt} \times HIGH_i + X'_{jt}\beta + \varepsilon_{ijt}\Big] \tag{27}$$

Table 4 shows the effects of immigration enforcement on the exports of labor-intensive commodities to other U.S. states, considering the destination enforcement intensity. Columns (2) and (4) show the results from my preferred specification with fixed effects and state controls. The results show no statistically significant difference between exports to other

[13]As with the main analysis, I use two measures of immigration enforcement intensity: the summary index and the summation index. I use different thresholds for these measures to create the $HIGH_j$ variable based on their respective median values.

[14]I first identify the maximum enforcement intensity for each state for four years and calculate the median value based on those enforcement values.

U.S. states based on their level of enforcement. This result is consistent across the use of two treatment indices.

However, this is not true for imports from other U.S. states. Table 5 shows the effects of enforcement intensity on the inward flow of labor-intensive commodities from other U.S. states, taking into account the origin enforcement intensity. Columns (2) and (4) show the results from my preferred specification with fixed effects and state controls. Looking at the results in Panel B using normalized enforcement index while using the monetary value of trade as the outcome variable, the results from column (2) show that while a one standard deviation increase in enforcement intensity leads to an increase of imports from U.S. states with below-median highest enforcement by almost 30.95 percent $((\exp(0.269) - 1) \times 100)$, the difference in FV imports between below- and above-median enforcement states is 20.87 percent $((\exp(-0.234) - 1) \times 100)$.[15]

This pattern persists, and the observed differences are wider, when using the total trade weight as an outcome variable, as shown in column (4). The results show that while imports from other U.S. states with below-median enforcement increase by 50.68 percent $((\exp(0.410) - 1) \times 100)$, the difference in imports from states with above-median enforcement intensity is 37.62 percent $((\exp(-0.471) - 1) \times 100)$.

Specifically for interstate imports, this result shows that while imports increase due to higher immigration enforcement, the imports only come from low enforcement intensity states, as high enforcement states would drop their exports themselves due to a reduction in production.

5.3 Effects on International Trade

Table 6 shows the results analyzing the effects of state-level immigration enforcement on the exports of fruits and vegetables using equation (24) and the USDA data on the cash receipts estimates from exports. I analyze effects on fruits, vegetables, and fruits and vegetables taken together. Columns (2), (4), and (6) show the results of my preferred specification with exporter-state and year fixed effects, and state controls.

I focus on Panel B, which uses the normalized enforcement index as the treatment. Column (2) shows that a one standard deviation increase in enforcement intensity is as-

[15] I cannot infer from these coefficients that the net import is negative (0.208-0.309) because the scale of imports from below- and above-median-enforcement states could vary drastically.

sociated with a 10.53 percent $((\exp(-0.081)-1)\times 100)$ decrease in international exports of fruits. Column (4) shows the effects on international vegetable exports. Although I see a negative coefficient, it is not statistically different from zero. Column (6) shows the effects on the combined exports of fruits and vegetables. I find that a one standard deviation increase in the enforcement index is associated with a 7.79 percent $((\exp(-0.081)-1)\times 100)$ decrease in the international exports of fruits and vegetables taken together, which is driven mainly through the reduction in the international exports of fruits. As Panel A shows, the magnitudes for the regressions using the non-normalized enforcement index as the treatment variable are similar, although slightly larger.

Table 7 shows the effects of immigration enforcement intensity on FV imports from Mexico (panel A) and Canada (panel B), two of the largest FV import partners for the United States. Columns (2) and (4) show results using my preferred specification with fixed effects and state controls in terms of monetary value and weight respectively. Panel A2 shows that a one standard deviation increase in enforcement intensity is associated with a 7.31 percent $((\exp(-0.076)-1)\times 100)$ decrease in FV imports from Mexico in terms of monetary value and a 5.54 percent $((\exp(-0.057)-1)\times 100)$ decrease in terms of weight. We, however, do not find any significant effects of enforcement intensity on the FV imports from Canada, as shown in Panel B, columns (2) and (4).

I further disentangle this effect using a slightly modified version of the import analysis regression. Instead of limiting the sample to only the SCTG code of 02, I include codes 01 to 09, which includes various agricultural products. I introduce the term L_k that equals 1 if the agricultural commodity is labor-intensive in production, which includes fruits and vegetables. The idea of this exercise is to analyze the relative effects of enforcement intensity on FVs compared to other non-labor-intensive agricultural products. I illustrate this regression in equation 28, where k indexes the commodity category. I also control for commodity category fixed effects, Λ_k.

$$EX_{ijkt} = exp\Big[\Gamma_{it} + \Psi_{ij} + \Lambda_k + \alpha_1 ENF_{jt} + \alpha_2 ENF_{jt} \times L_k + X'_{jt}\beta + \varepsilon_{ijkt}\Big] \tag{28}$$

Table 8 shows the effects of this specification. Panel A2, column (4) shows that while using imports in terms of weight as the outcome variable, although immigration enforcement intensity significantly reduces the import of non-FVs from Mexico by 14.01 percent

$((\exp(-0.076)-1)\times 100)$, FV imports increase by 10.6 percent $((\exp(-0.076)-1)\times 100)$ percent (0.246-0.140). This effect is, however, not observed while using import in terms of monetary value as the outcome variable, although the coefficients are in similar directions. I do not find any significant effects on imports from Canada.

5.4 Placebo Tests

In the primary analysis of the effects of immigration enforcement on interstate FV trade and the international FV imports, I used the FAF-5 data, precisely the sample of product code "03" which includes labor-intensive commodities like fruits and vegetables. For the international exports analysis, I used the subsample for fruits and vegetables (separately and together) from the USDA data on the cash receipts estimates from foreign exports. 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 crops from the FAF-5 data for interstate trade and international imports and the sample of corn and soybean (taken separately) from the USDA cash receipts estimates for exports. The production of cereal crops, corn, and soybeans is highly capital-intensive. Although I call it placebo 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.

Tables 9 and 10 show the effects of immigration enforcement on the interstate export and interstate import of cereal crops, respectively, using the FAF-5 data. Columns (2) and (4) in both tables illustrate the results from my preferred model with the fixed effects and state controls. I do not see any statistically significant effects of immigration enforcement intensity on interstate exports or imports.

Table 11 shows the effects of immigration enforcement intensity on the international export of corn and soybean. Columns (2) and (4), with the preferred specification, show no statistically significant association between immigration enforcement intensity and the international exports of the commodities. Finally, table 12 shows the results of the placebo test for imports from Mexico and Canada using cereal crops. I do not find any statistically significant effects, as per columns A2 and B2, columns (2) and (4), that show results from the preferred specification.

5.5 Police vs Employment Enforcement: What is Driving the Effects?

So far, I have used the aggregated immigration enforcement index as the treatment variable. I also run regressions using (1) weighted police- and employment-based enforcement intensities and (2) individual weighted policy variables as the treatment variables. Police-based enforcement includes the state- and county-level 287g acts, Secure Communities, and the Omnibus Bill. The employment-based enforcement consists of the E-Verify.

Table 13 shows the effects of these policies on interstate FV exports. I only discuss the statistically significant coefficients from the set of regressions. From columns (1) and (3), I find that although both police- and employment-based enforcement measures decrease FV interstate exports, only the police-based enforcement is statistically significant. In terms of monetary value, column (1) shows that a one standard deviation increase in police-based enforcement measures is associated with a 15.63 percent $((\exp(-0.170)-1)\times 100)$ drop in interstate FV exports, which is statistically significant at a 5 percent level. In terms of weight, column (3) shows that the increase is associated with a similar 16.88 percent $((\exp(-0.185)-1)\times 100)$ drop in interstate FV exports.

In terms of specific policies, the Omnibus Bill is the only policy that has a consistent negative effect on interstate FV exports in terms of both monetary value and weight. In terms of monetary value, a one standard deviation increase in its adopted is associated with a 39.7 percent decrease in interstate FV exports. The county-level 287g policy is associated with a 34.9 percent drop in interstate FV exports in terms of weight, but the coefficient on the policy variable is not statistically different from zero for monetary value, although it shows a negative sign.

Table 14 shows the effects of these policies on the interstate FV imports. I only discuss the statistically significant coefficients from the set of regressions. From columns (1) and (3), I find that police-based enforcement has a statistically significant increase of interstate FV imports by 23.7 percent in terms of monetary value and 30.8 percent in terms of weight, which is driving the overall positive interstate FV imports effects that I observed earlier. Controlling for the police-based enforcement, the employment-based enforcement has a negative association with interstate FV imports but which is not statistically significant.

Columns (2) and (4) show the effects of specific policies on interstate FV imports. I see that only the Omnibus Bill has a consistently significant positive association with interstate FV imports, which is 32.5 percent in terms of monetary value and 55.8 percent in terms of weight.

5.6 Addressing the Potential Endogeneity of Enforcement Intensity

One potential threat to identification is the endogeneity of immigration enforcement intensity with respect to agricultural outcomes. To address this concern, I conduct two additional sets of analyses. First, I follow a strategy similar to Ferrara et al. (2012) by modeling the timing of adopting stricter immigration policies at the state level as a function of agricultural outcomes before implementing these measures. Specifically, I construct a variable that identifies the year each state's enforcement index first became positive. I then examine whether agricultural outcomes in the baseline year can predict the year of adoption of stricter immigration enforcement. To do so, I run equation 29 where $EnfYear_s$ is the year the enforcement variable value for state s turned positive from zero. $X_{s,2002}$ is a vector of baseline-year state-level characteristics.

$$EnfYear_s = \alpha + X'_{s,2002}\beta + \varepsilon_s \tag{29}$$

Table 15 shows the results of this analysis. Columns (1)-(3) use the 2002 values of the independent variables, while columns (4)-(6) use the difference between 1997 and 2002 values for the variables. Columns (1) and (4) use the total FV exports in dollars as the explanatory variable. Columns (2) and (5) use the Bartik-style measure of local economic growth as the explanatory variable. Columns (3) and (6) use FV exports (in dollars), Bartik-style measure, minimum wage, the adverse effect wage rate, and the housing price index as the explanatory variables. The results show that I do not find a statistically significant association of any of these variables on the first year of immigration enforcement adoption.

6 Conclusion

This paper investigates the effects of immigration enforcement on U.S. agricultural trade, with a particular focus on labor-intensive fruit and vegetable production. By leveraging state-level variations in enforcement intensity, I analyze how shifts in farm labor availability, driven by immigration policies, influence both domestic and international trade patterns. The results indicate that heightened enforcement reduces the domestic supply of U.S.-grown FV products. To mitigate the reduction in local FV supply, states with higher enforcement increase their imports from lower enforcement states.

I also observe a significant effect of immigration enforcement on international FV exports. However, contrary to expectations, I do not find evidence that the rise in international FV imports is related to the changing labor dynamics. In fact, I find that immigration enforcement negatively affects FV imports from Mexico, the largest FV import partner for the United States. Other factors, such as trade agreements and lower production costs in countries of origin, might explain the significant rise in FV imports over the last few decades.

References

[1] Amuedo-Dorantes, C. and Arenas-Arroyo, E. (2019). Immigration enforcement and children's living arrangements. Journal of Policy Analysis and Management, 38(1):11–40.

[2] Amuedo-Dorantes, C., Arenas-Arroyo, E., and Sevilla, A. (2018). Immigration enforcement and economic resources of children with likely unauthorized parents. Journal of Public Economics, 158:63–78.

[3] Amuedo-Dorantes, C., Arenas-Arroyo, E., and Wang, C. (2020). Is immigration enforcement shaping immigrant marriage patterns? Journal of Public Economics, 190:104242.

[4] Amuedo-Dorantes, C., Lofstrom, M., and Wang, C. (2022). Immigration policy and the rise of self-employment among mexican immigrants. Industrial and Labor Relations Review, 75(5):1189–1214.

[5] Amuedo-Dorantes, C. and Lopez, M. J. (2017a). The hidden educational costs of intensified immigration enforcement. Southern Economic Journal, 84(1):120–154.

[6] Amuedo-Dorantes, C. and Lopez, M. J. (2017b). Interior immigration enforcement and political participation of us citizens in mixed-status households. Demography, 54(6):2223–2247.

[7] Amuedo-Dorantes, C., Pozo, S., and Puttitanun, T. (2015). Immigration enforcement, parent–child separations, and intent to remigrate by central american deportees. Demography, 52(6):1825–1851.

[8] Amuedo-Dorantes, C. and Puttitanun, T. (2018). Undocumented youth in limbo: the impact of america's immigration enforcement policy on juvenile deportations. Journal of Population Economics, 31:597–626.

[9] Amuedo-Dorantes, C., Puttitanun, T., and Martinez-Donate, A. P. (2019). Deporting "bad hombres"? the profile of deportees under widespread versus prioritized enforcement. International Migration Review, 53(2):518–547.

[10] Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. American Economic Review, 93(1):170–192.

[11] Arteaga, J. and Shenoy, A. (2023). Declining mobility among mexican-born workers in the us labor force.

[12] Auboin, M. and Ruta, M. (2013). The relationship between exchange rates and international trade: a literature review. World Trade Review, 12(3):577–605.

[13] Bacchetta, P. and Van Wincoop, E. (2000). Does exchange-rate stability increase trade and welfare? American Economic Review, 90(5):1093–1109.

[14] Bartik, T. J. (1992). The effects of state and local taxes on economic development: A review of recent research. Economic Development Quarterly, 6(1):102–111.

[15] Bohn, S., Lofstrom, M., and Raphael, S. (2014). Did the 2007 legal arizona workers act reduce the state's unauthorized immigrant population? Review of Economics and Statistics, 96(2):258–269.

[16] Castillo, M. and Charlton, D. (2023). Housing booms and h-2a agricultural guest worker employment. American Journal of Agricultural Economics, 105(2):709–731.

[17] Charlton, D. and Kostandini, G. (2021). Can technology compensate for a labor shortage? effects of 287 (g) immigration policies on the us dairy industry. American Journal of Agricultural Economics, 103(1):70–89.

[18] Charlton, D., Kostandini, G., and Luo, T. (2023). Immigration policy and labor contractors: Evidence from 287 (g) and farm labor markets.

[19] Charlton, D. and Taylor, J. E. (2016). A declining farm workforce: Analysis of panel data from rural mexico. American Journal of Agricultural Economics, 98(4):1158–1180.

[20] Charlton, D. and Taylor, J. E. (2020). Rural school access and the agricultural transformation. Agricultural Economics, 51(5):641–654.

[21] Clemens, M. A., Lewis, E. G., and Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. American Economic Review, 108(6):1468–1487.

[22] Costinot, A. (2009). An elementary theory of comparative advantage. Econometrica, 77(4):1165–1192.

[23] Cruz, F., Kostandini, G., Mykerezi, E., Jordan, J., and Tanellari, E. (2022). The effects of e-verify on the share of labor-intensive and capital-intensive crops: Evidence from farm-level data. Agribusiness, 38(3):660–678.

[24] Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., and Pasteris, P. P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous united states. International Journal of Climatology: a Journal of the Royal Meteorological Society, 28(15):2031–2064.

[25] Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. American economic review, 97(1):354–385.

[26] Devadoss, S. and Luckstead, J. (2011). Implications of immigration policies for the us farm sector and workforce. Economic Inquiry, 49(3):857–875.

[27] East, C. N., Hines, A. L., Luck, P., Mansour, H., and Velasquez, A. (2023). The labor market effects of immigration enforcement. Journal of Labor Economics, 41(4):957–996.

[28] East, C. N. and Velásquez, A. (2022). Unintended consequences of immigration enforcement: Household services and high-educated mothers' work. Journal of Human Resources.

[29] Fan, M., Gabbard, S., Alves Pena, A., and Perloff, J. M. (2015). Why do fewer agricultural workers migrate now? American Journal of Agricultural Economics, 97(3):665–679.

[30] Farm Credit East (2017). The farm labor issue: Economic impact in new york state. https://www.northcountrypublicradio.org/pdfs/the-farm-labor-issue-ny.pdf. Accessed: 05-01-2024.

[31] Ferrara, E. L., Chong, A., and Duryea, S. (2012). Soap operas and fertility: Evidence from brazil. American Economic Journal: Applied Economics, 4(4):1–31.

[32] Fisher, D. U. and Knutson, R. D. (2013). Uniqueness of agricultural labor markets. American Journal of Agricultural Economics, 95(2):463–469.

[33] Geraci, V. J. and Prewo, W. (1977). Bilateral trade flows and transport costs. The review of Economics and Statistics, pages 67–74.

[34] Haveman, J. and Hummels, D. (2004). Alternative hypotheses and the volume of trade: the gravity equation and the extent of specialization. Canadian Journal of Economics/Revue canadienne d'économique, 37(1):199–218.

[35] Hertz, T. and Zahniser, S. (2013). Is there a farm labor shortage? American Journal of Agricultural Economics, 95(2):476–481.

[36] Hilton, R. S. (1984). Commodity trade and relative returns to factors of production. Journal of International Economics, 16(3-4):259–270.

[37] Hummels, D. (2007). Transportation costs and international trade in the second era of globalization. Journal of Economic perspectives, 21(3):131–154.

[38] Ifft, J. and Jodlowski, M. (2022). Is ice freezing us agriculture? farm-level adjustment to increased local immigration enforcement. Labour Economics, 78:102203.

[39] Johnson, R. (2014). The US trade situation for fruit and vegetable products. Congressional Research Service Washington, DC.

[40] Kostandini, G., Mykerezi, E., and Escalante, C. (2014). The impact of immigration enforcement on the us farming sector. American Journal of Agricultural Economics, 96(1):172–192.

[41] Krogstad, J. M., Passel, J. S., and Cohn, D. (2017). facts about illegal immigration in the us. Pew Research Center, 19.

[42] Luo, T. and Kostandini, G. (2022). Stringent immigration enforcement and responses of the immigrant-intensive sector: Evidence from e-verify adoption in arizona. American Journal of Agricultural Economics, 104(4):1411–1434.

[43] Luo, T. and Kostandini, G. (2023). Omnibus or ominous immigration laws? immigration policy and mental health of the hispanic population. Health Economics, 32(1):90–106.

[44] Luo, T., Kostandini, G., and Jordan, J. L. (2023). Stringent immigration enforcement and the farm sector: Evidence from e-verify adoption across states. Applied Economic Perspectives and Policy, 45(2):1211–1232.

[45] Martin, P. (2017a). Immigration and farm labor: challenges and opportunities.

[46] Martin, P. (2017b). Trump, immigration, and agriculture. Choices, 32(1):1–5.

[47] Martin, P. and Calvin, L. (2011). Labor trajectories in california's produce industry.

[48] Martin, P. L. (2003). Promise unfulfilled: Unions, immigration and the farm workers. Cornell University Press.

[49] Martin, P. L. and Taylor, J. E. (1998). Poverty amid prosperity: Farm employment, immigration, and poverty in california. American journal of agricultural economics, 80(5):1008–1014.

[50] Nunn, N. and Trefler, D. (2014). Domestic institutions as a source of comparative advantage. Handbook of international economics, 4:263–315.

[51] Orrenius, P. M. and Zavodny, M. (2015). The impact of e-verify mandates on labor market outcomes. Southern Economic Journal, 81(4):947–959.

[52] Orrenius, P. M. and Zavodny, M. (2016). Do state work eligibility verification laws reduce unauthorized immigration? IZA Journal of Migration, 5(1):5.

[53] Richards, T. J. (2018). Immigration reform and farm labor markets. American Journal of Agricultural Economics, 100(4):1050–1071.

[54] Richards, T. J. and Patterson, P. M. (1998). Hysteresis and the shortage of agricultural labor. American Journal of Agricultural Economics, 80(4):683–695.

[55] Rutledge, Z. and Mérel, P. (2023). Farm labor supply and fruit and vegetable production. American Journal of Agricultural Economics, 105(2):644–673.

[56] Santacreu, A. M. (2015). Innovation, diffusion, and trade: Theory and measurement. Journal of Monetary Economics, 75:1–20.

[57] Santeramo, F. G. and Lamonaca, E. (2019). The effects of non-tariff measures on agri-food trade: A review and meta-analysis of empirical evidence. Journal of Agricultural Economics, 70(3):595–617.

[58] Shepherd, B. et al. (2013). The gravity model of international trade: A user guide.

[59] Silva, J. S. and Tenreyro, S. (2006). The log of gravity. The Review of Economics and statistics, 88(4):641–658.

[60] Smith, D. J. (2023). What drives undocumented immigration? policy, economic, and social factors in the us and mexico. Policy, Economic, and Social Factors in the Us and Mexico.

[61] Svaleryd, H. and Vlachos, J. (2005). Financial markets, the pattern of industrial specialization and comparative advantage: Evidence from oecd countries. European Economic Review, 49(1):113–144.

[62] Tong, L. A., Pham, C. S., and Ulubaşoğlu, M. A. (2019). The effects of farm subsidies on farm exports in the united states. American Journal of Agricultural Economics, 101(4):1277–1304.

[63] U.S. Department of Commerce (2023). Mexico - agriculture. Accessed: 2024-07-01.

[64] USDA ERS (2023). Imports make up growing share of u.s. fresh fruit and vegetable supply. https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=107008. Accessed: 09-24-2024.

[65] USDA NASS (2024). 2022 census of agriculture. Accessed: 2024-07-01.

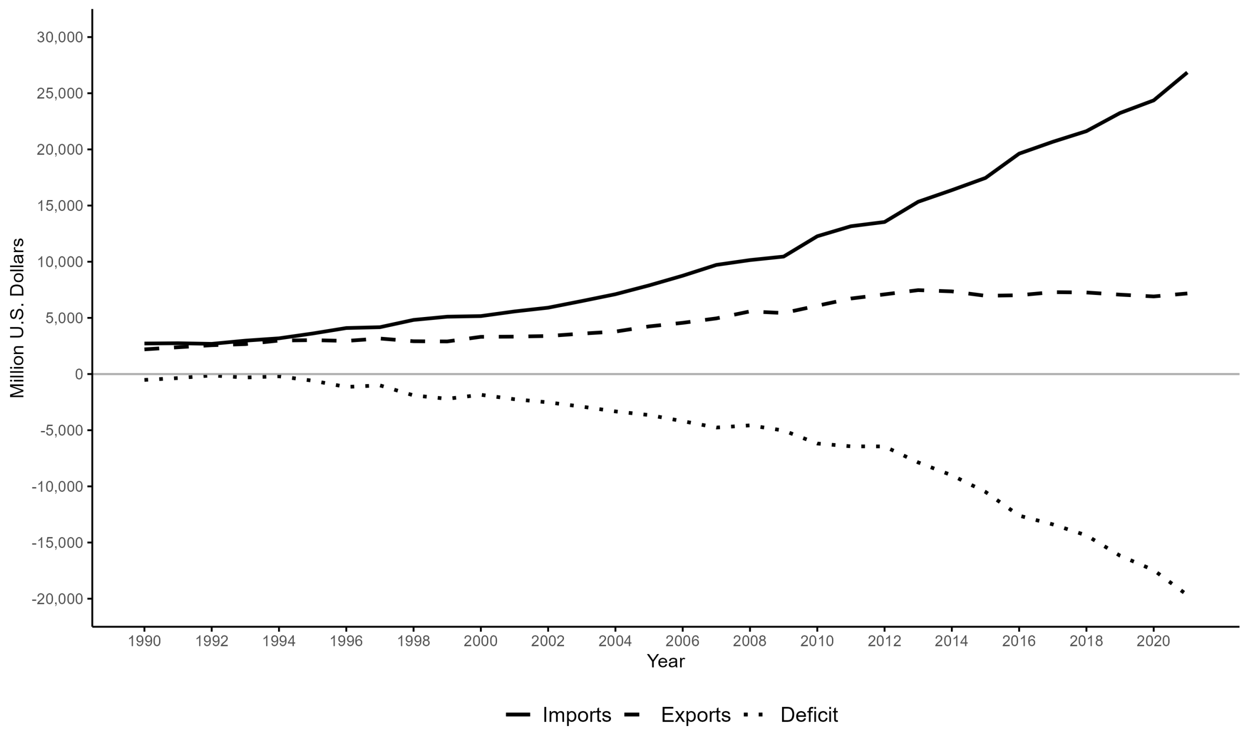
[66] Yotov, Y. V., Piermartini, R., Larch, M., et al. (2016). An advanced guide to trade policy analysis: The structural gravity model. WTO iLibrary.

[67] Zahniser, S., Hertz, T., Dixon, P., and Rimmer, M. (2012). Immigration policy and its possible effects on us agriculture and the market for hired farm labor: a simulation analysis. American Journal of Agricultural Economics, 94(2):477–482.

[68] Zahniser, S., Taylor, J. E., Hertz, T., and Charlton, D. (2018). Farm labor markets in the united states and mexico pose challenges for us agriculture.

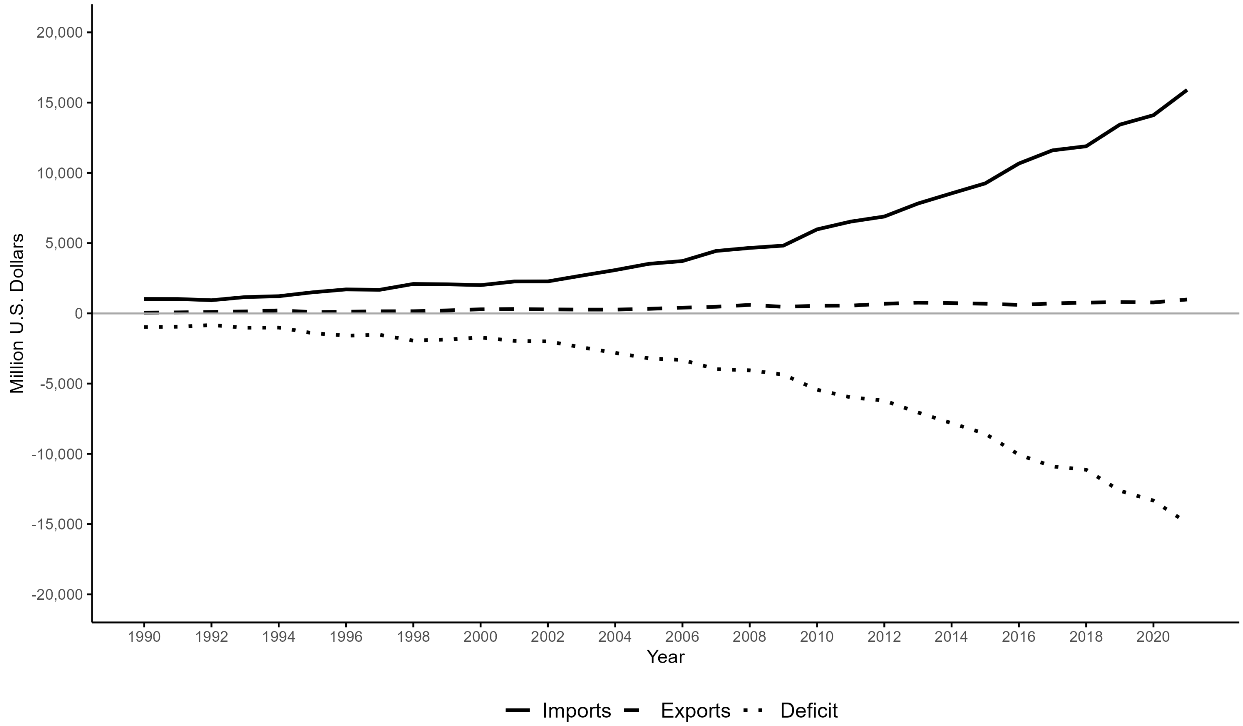
Figures

Figure 1: Total fresh fruit and vegetable trade with foreign partners, 1990-2021



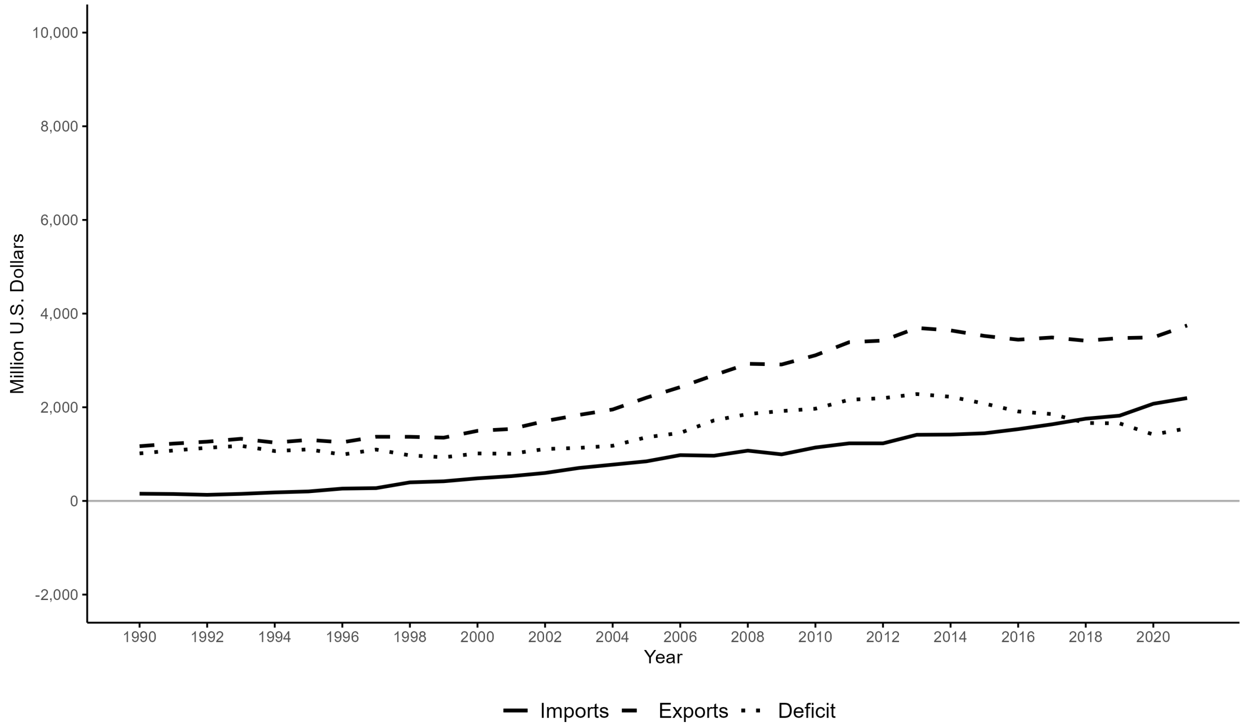
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 2: Fresh fruit and vegetable trade with Mexico, 1990-2021



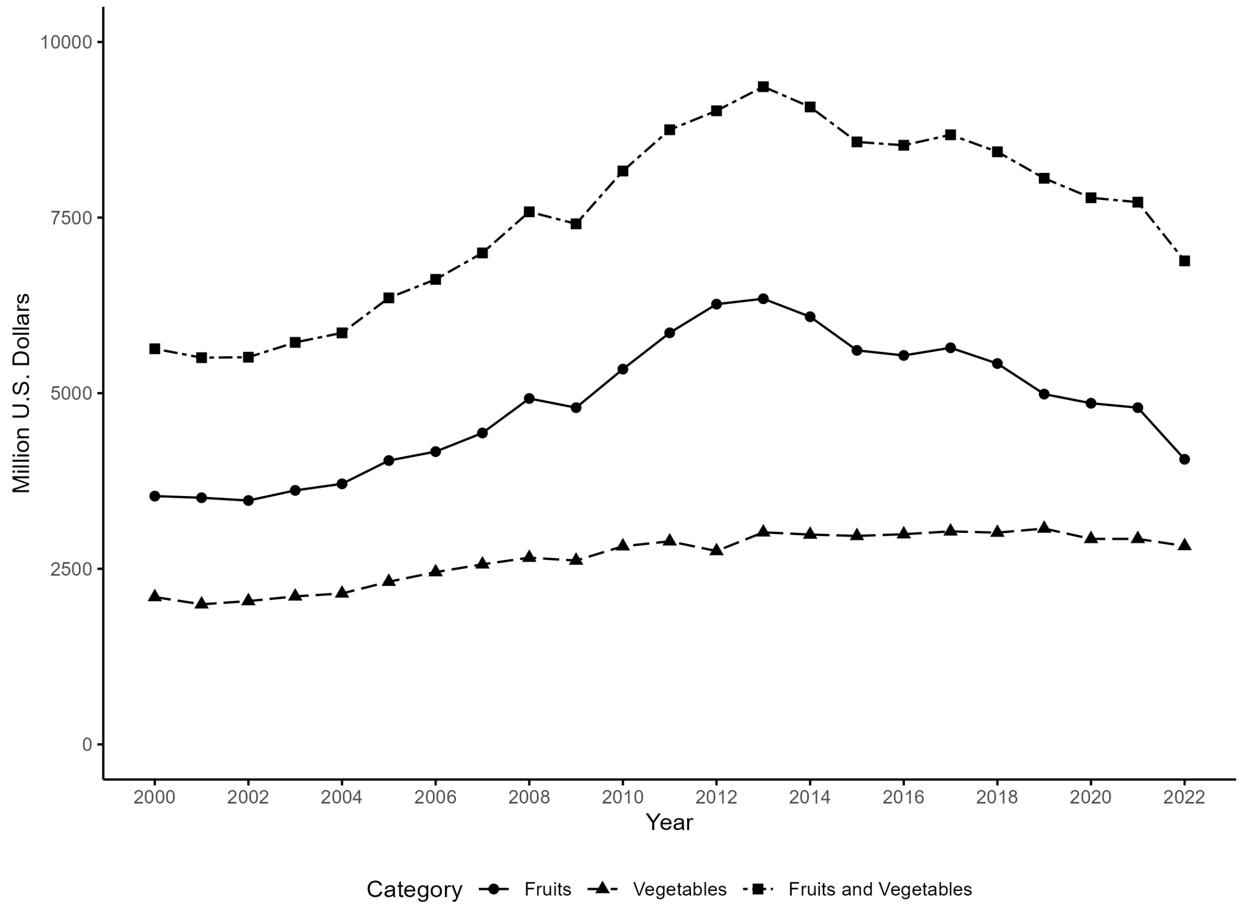
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 3: Fresh fruit and vegetable trade with Canada, 1990-2021



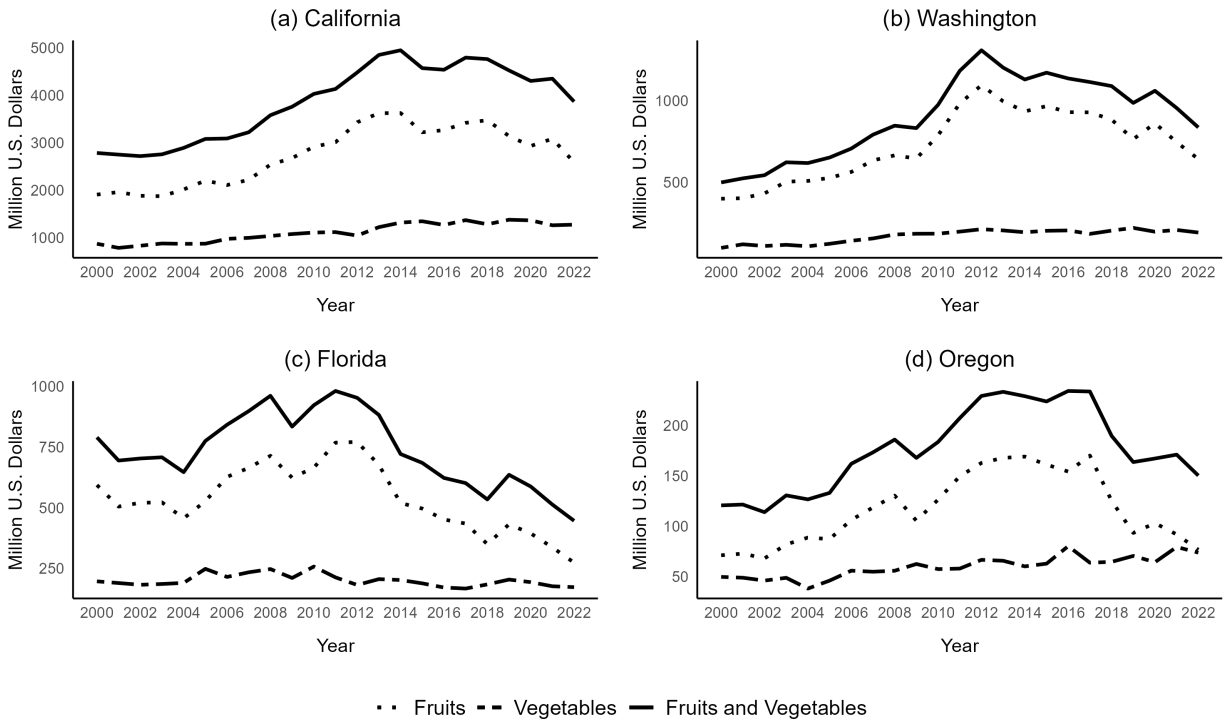
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 4: Fresh fruit and vegetable trade with Canada, 1990-2021



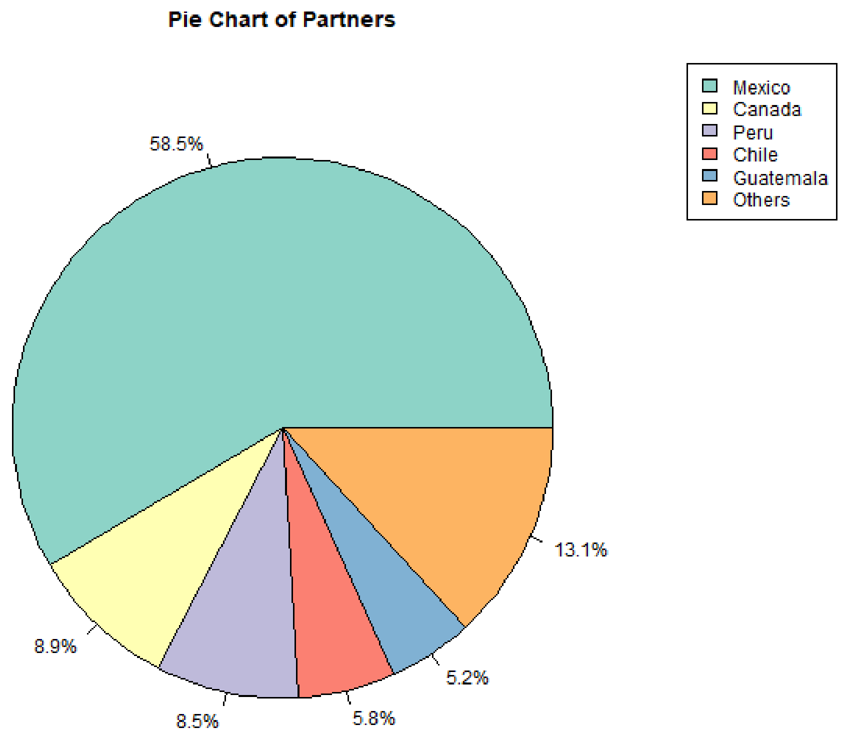
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 5: Fresh fruit and vegetable exports, Four Largest Exporters, 2000-2022



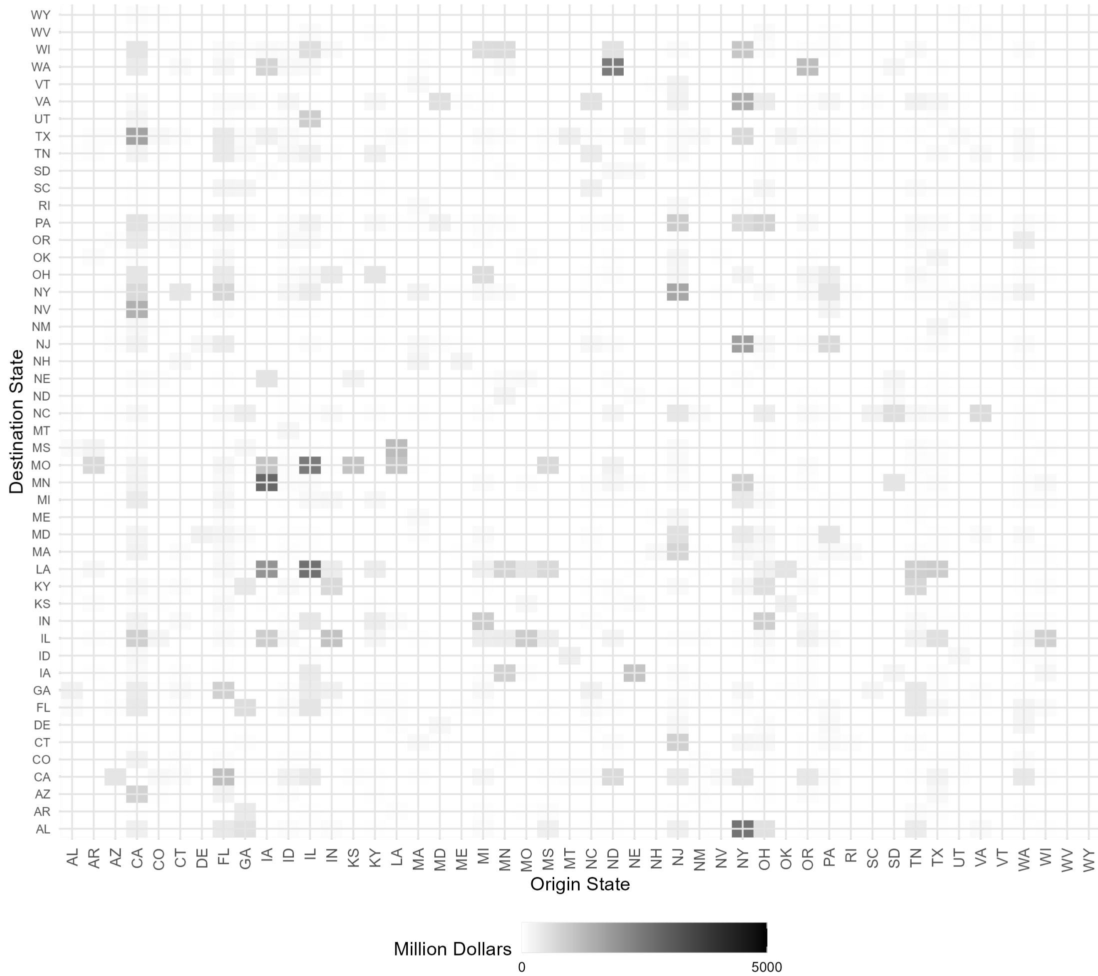
Note: Created using the data from the USDA. The values are in 2022 US Dollars.

Figure 6: Import partners for fresh fruits and vegetables for the United States, 2022



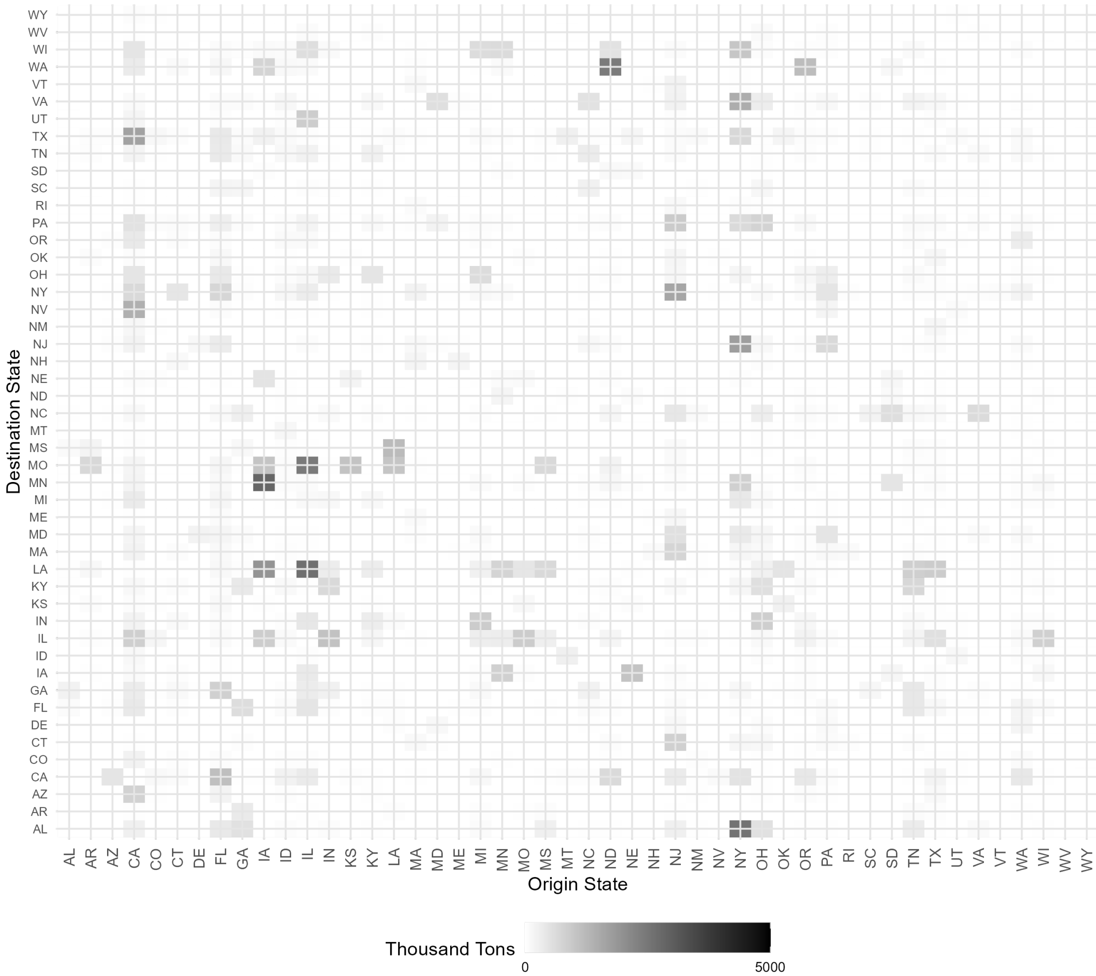
Note: Data comes from the USDA FSA.

Figure 7: Domestic Interstate Trade, in Million Dollars, 2012



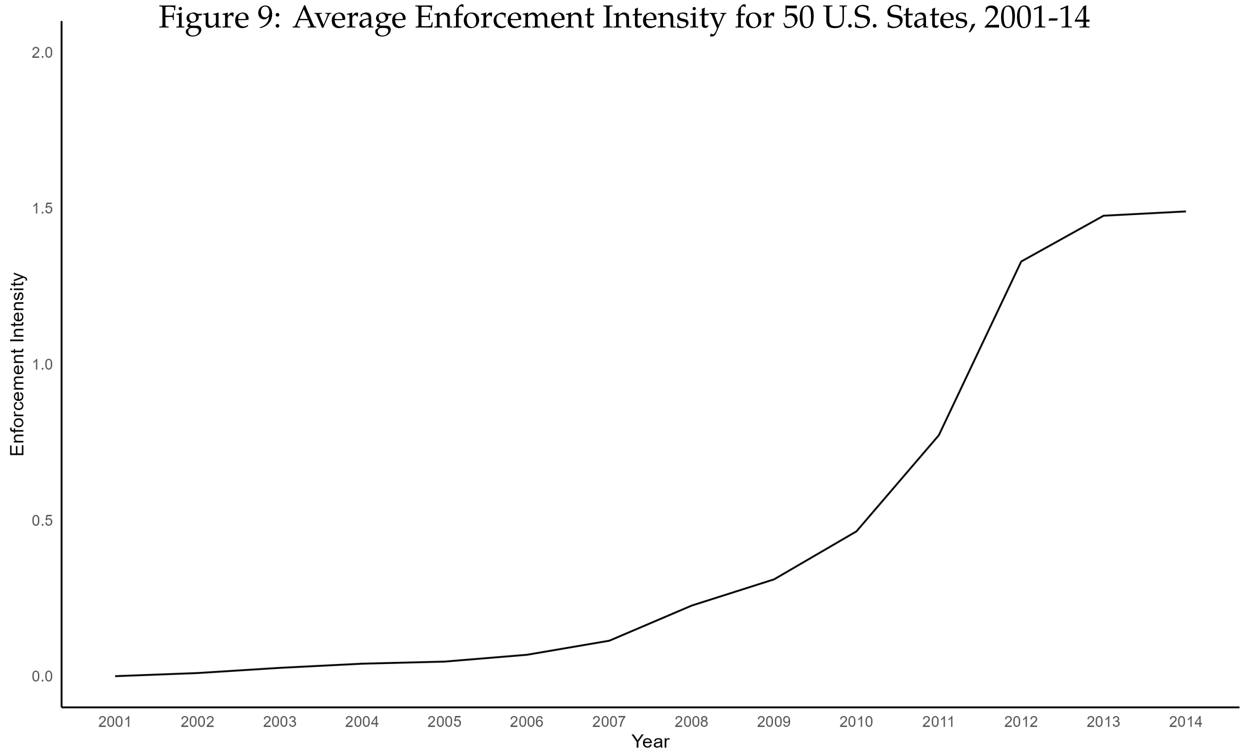
Note: Created using the data from the Freight Analysis Framework (FAF-5). The values are in 2022 US Dollars.

Figure 8: Domestic Interstate Trade, in Thousand Tons, 2012



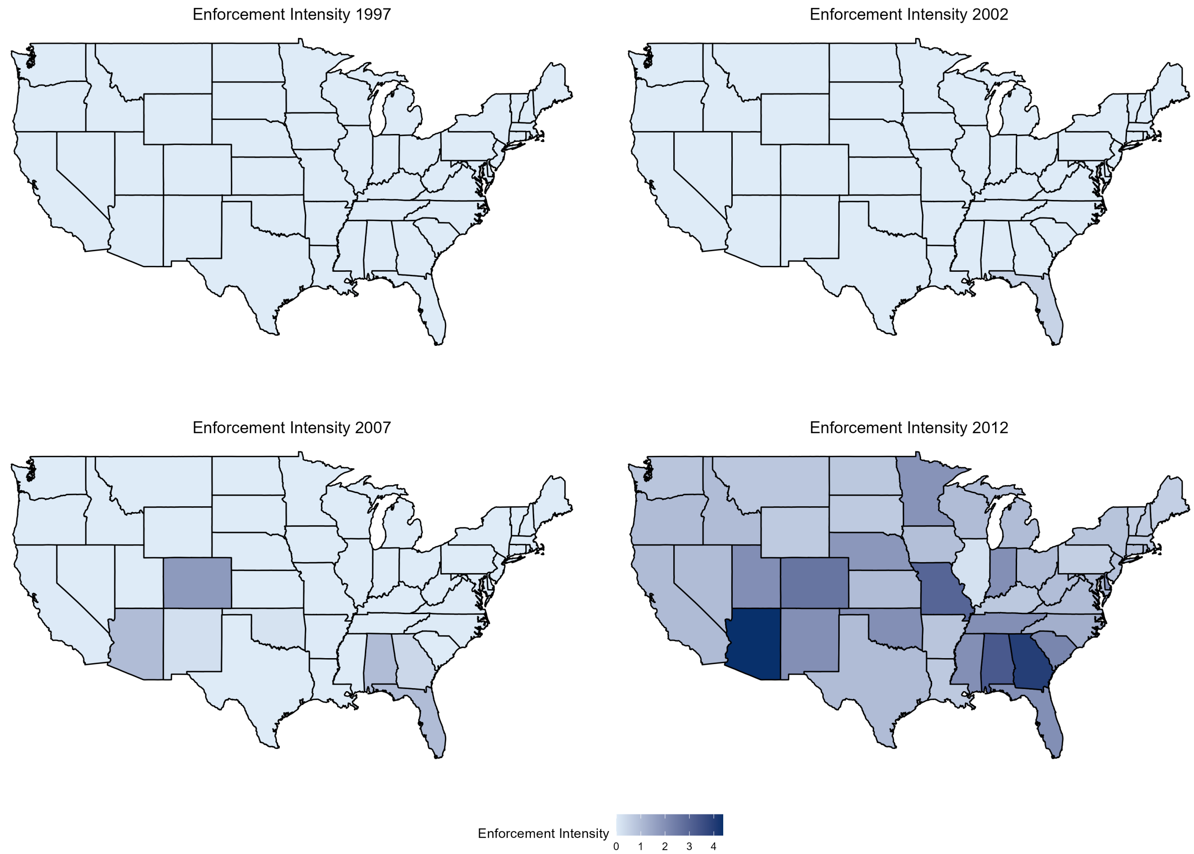
Note: Created using the data from the Freight Analysis Framework (FAF-5). The values are in 2022 US Dollars.

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



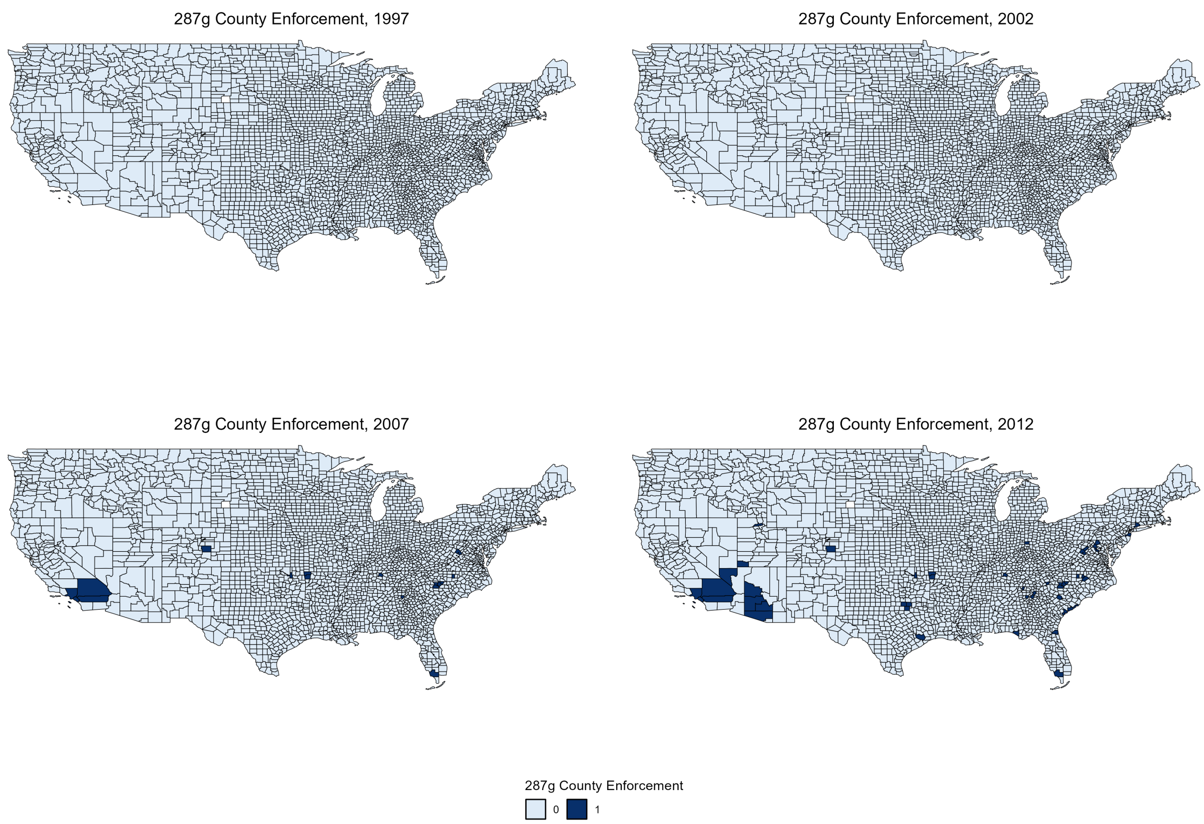
Note: This figure shows the average enforcement intensity across 50 U.S. states from 2001 to 2014. The enforcement intensity variable is created using equations (20) and (21).

Figure 10: Spatiotemporal Variations in Enforcement intensity



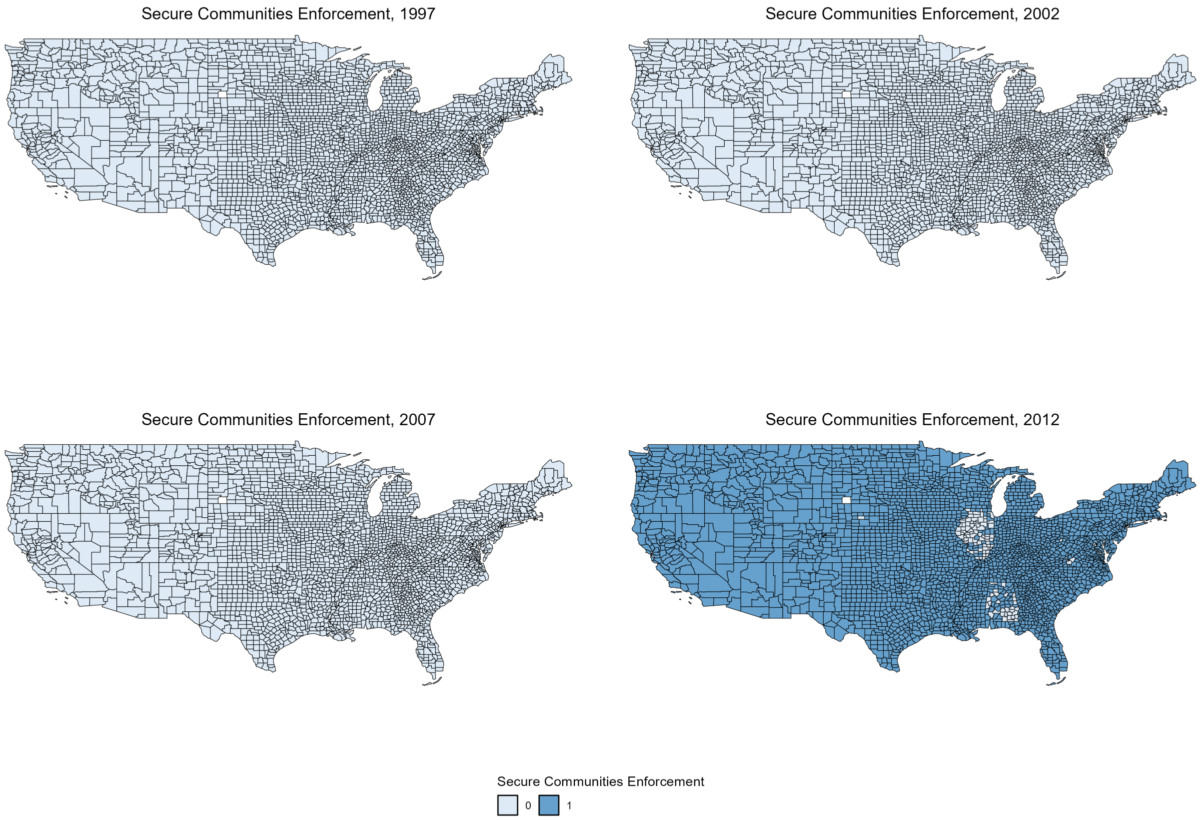
Note: This figure shows the enforcement intensity across 48 contiguous U.S. states for 1997, 2002, and 2007, and 2012. The enforcement intensity variable is created using equations (20) and (21).

Figure 11: Spatiotemporal Variations in 287g County Enforcement



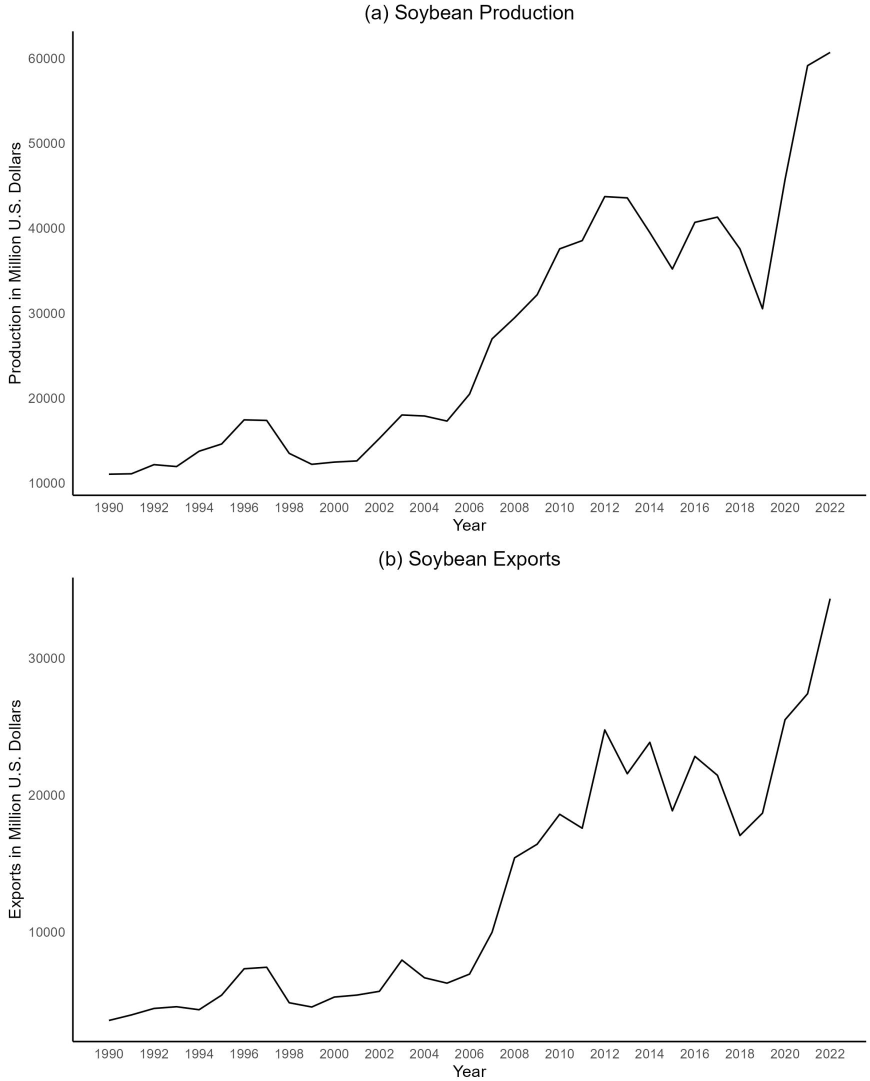
Note: This figure shows counties with active Immigration and National Act 287g county-level policy across 50 U.S. states for 1997, 2002, and 2007, and 2012.

Figure 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: 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.

Tables

Table 1: Effects on Labor Expenses and Agricultural Production

	Labor Exp %	Labor Exp	Crop Prod	FV Prod
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	-0.033*	-0.098***	-0.009	-0.088***
	(0.016)	(0.036)	(0.034)	(0.029)
Panel B: Normalized summary index				
Enforcement	-0.026**	-0.076***	-0.008	-0.069***
	(0.012)	(0.027)	(0.026)	(0.022)
Control variables	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	164	164	188	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, for column (3) is the total crop production, and for column (4) is the total production of fruits, nuts, and vegetables, all of which are taken from the Census of Agriculture from USDA National Agricultural Statitical Service (NASS). The primary explanatory variable for Panel A is the summation index created in equation (21), and that for Panel B is the normalized version of the index. The regressions are weighted by the baseline value for fruits, nuts, and vegetables production at the state level for columns (1), (2), and (4). The regression in column (3) is weighted by the baseline value of the total crop production 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 Interstate Export of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	-0.169***	-0.180***	-0.151*	-0.194**
	(0.060)	(0.061)	(0.078)	(0.076)
Panel B: Normalized summary index				
Enforcement	-0.133***	-0.141***	-0.118*	-0.152**
	(0.047)	(0.048)	(0.061)	(0.060)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Importer-by-year fixed effects	Yes	Yes	Yes	Yes
N	8,392	8,392	8,500	8,500

The outcome variables are the exports from a U.S. state to other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with importer-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 3: Effects on Interstate Import of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	0.105*	0.162***	0.124	0.184**
	(0.054)	(0.057)	(0.087)	(0.093)
Panel B: Normalized summary index				
Enforcement	0.081*	0.126***	0.096	0.143**
	(0.042)	(0.044)	(0.068)	(0.072)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
N	8,392	8,392	8,500	8,500

The outcome variables are the imports for a U.S. state from other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 4: Effects on Interstate Export of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	-0.123	-0.141	-0.063	-0.089
	(0.093)	(0.101)	(0.116)	(0.110)
Enforcement × High Importer Enforcement	-0.079	-0.067	-0.175	-0.217
	(0.124)	(0.127)	(0.161)	(0.166)
Panel B: Normalized summary index				
Enforcement	-0.096	-0.111	-0.050	-0.070
	(0.073)	(0.079)	(0.091)	(0.087)
Enforcement × High Importer Enforcement	-0.062	-0.052	-0.137	-0.170
	(0.097)	(0.100)	(0.126)	(0.130)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Importer-by-year fixed effects	Yes	Yes	Yes	Yes
N	8,392	8,392	8,500	8,500

The outcome variables are the exports from a U.S. state to other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. High Importer Enforcement is a binary dummy variable that equals 1 if the highest enforcement intensity at the state level (in 2012) for the importer state is above the median value. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with importer-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 5: Effects on Interstate Import of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	0.287***	0.347***	0.480***	0.528***
	(0.110)	(0.105)	(0.143)	(0.136)
Enforcement × High Exporter Enforcement	-0.294**	-0.301***	-0.613***	-0.607***
	(0.121)	(0.111)	(0.159)	(0.142)
Panel B: Normalized summary index				
Enforcement	0.222***	0.268***	0.371***	0.408***
	(0.085)	(0.081)	(0.111)	(0.105)
Enforcement × High Exporter Enforcement	-0.227**	-0.233***	-0.474***	-0.470***
	(0.094)	(0.086)	(0.123)	(0.110)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
N	8,392	8,392	8,500	8,500

The outcome variables are the imports from a U.S. state to other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. High Exporter Enforcement is a binary dummy variable that equals 1 if the highest enforcement intensity at the state level (in 2012) for the exporter state is above the median value. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 6: Effects on International Export of Fruits and Vegetables

	Fruits		Vegetables		Fruits & Vegetables	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Enforcement index						
Enforcement	-0.158***	-0.163***	-0.019	-0.017	-0.120***	-0.119**
	(0.037)	(0.026)	(0.032)	(0.033)	(0.041)	(0.047)
Panel B: Normalized enforcement index						
Enforcement	-0.108***	-0.111***	-0.013	-0.012	-0.082***	-0.081**
	(0.025)	(0.017)	(0.022)	(0.023)	(0.028)	(0.032)
Control variables	No	Yes	No	Yes	No	Yes
Exporter fixed effects	No	Yes	Yes	No	Yes	Yes
Year fixed effects	No	Yes	Yes	No	Yes	Yes
N	552	552	528	528	564	564

Outcome variables are the exports of fruits (columns 1-2), vegetables (columns 3-4), and fruits and vegetables (5-6) from a U.S. state to the world in terms of the total monetary values in 2022 million U.S. dollars from the state-level USDA cash receipts estimates of exports. The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2), (4) and (6) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the baseline value of the total state-level exports. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 7: Effects on International Import of Fruits and Vegetables from Mexico and Canada

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Imports from Mexico				
Panel A1: Enforcement index				
Enforcement	-0.057***	-0.108***	-0.081***	-0.081***
	(0.016)	(0.014)	(0.002)	(0.006)
Panel A2: Normalized enforcement index				
Enforcement	-0.039***	-0.076***	-0.054***	-0.057***
	(0.010)	(0.010)	(0.001)	(0.005)
Panel B: Imports from Canada				
Panel B1: Enforcement index				
Enforcement	0.016	0.023	-0.031	-0.018
	(0.042)	(0.025)	(0.041)	(0.023)
Panel B2: Normalized enforcement index				
Enforcement	0.004	0.009	-0.028	-0.017
	(0.030)	(0.015)	(0.027)	(0.014)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
N	192	192	192	192

The outcome variables are the imports for a U.S. state from other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 8: Effects on International Import of Fruits and Vegetables from Mexico and Canada

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Imports from Mexico				
Panel A1: Enforcement index				
Enforcement	-0.154	-0.153	-0.220*	-0.189*
	(0.117)	(0.104)	(0.126)	(0.112)
Enforcement × Labor Intensive	0.149	0.149	0.280**	0.276**
	(0.139)	(0.137)	(0.131)	(0.125)
Panel A2: Normalized enforcement index				
Enforcement	-0.122	-0.121	-0.175*	-0.151*
	(0.093)	(0.082)	(0.100)	(0.089)
Enforcement × Labor Intensive	0.118	0.118	0.223**	0.220**
	(0.110)	(0.108)	(0.104)	(0.099)
Panel B: Imports from Canada				
Panel B1: Enforcement index				
Enforcement	-0.115*	-0.090	-0.081	-0.069
	(0.069)	(0.056)	(0.082)	(0.080)
Enforcement × Labor Intensive	0.026	0.026	-0.057	-0.057
	(0.094)	(0.093)	(0.113)	(0.113)
Panel B2: Normalized enforcement index				
Enforcement	-0.145*	-0.113	-0.102	-0.086
	(0.087)	(0.071)	(0.104)	(0.101)
Enforcement × Labor Intensive	0.033	0.033	-0.071	-0.071
	(0.118)	(0.117)	(0.143)	(0.142)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
Product-type fixed effects	Yes	Yes	Yes	Yes
N	1,656	1,656	1,656	1,656

The outcome variables are the imports for a U.S. state from other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 9: Placebo Test: Effects on Interstate Export of Cereal Crops

	Corn		Soybean	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	-0.082	-0.083	-0.120	-0.115
	(0.141)	(0.140)	(0.151)	(0.145)
Panel B: Normalized summary index				
Enforcement	-0.064	-0.065	-0.094	-0.090
	(0.110)	(0.109)	(0.118)	(0.113)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Importer-by-year fixed effects	Yes	Yes	Yes	Yes
N	5,496	5,496	5,512	5,512

The outcome variables are the exports from a U.S. state to other U.S. states in terms of the total monetary values of cereal crops in 2022 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with importer-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 10: Placebo Test: Effects on Interstate Import of Cereal Crops

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	-0.082	-0.104	0.023	-0.000
	(0.105)	(0.109)	(0.128)	(0.129)
Panel B: Normalized summary index				
Enforcement	-0.081	-0.081	-0.000	-0.000
	(0.084)	(0.084)	(0.100)	(0.100)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
N	5,490	5,490	5,506	5,506

The outcome variables are the imports for a U.S. state from other U.S. states in terms of the total monetary values of cereal crops in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 11: Placebo Test: Effects on International Export of Corn and Soybean

	Corn		Soybean	
	(1)	(2)	(3)	(4)
Panel A: Enforcement index				
Enforcement	0.054	0.036	0.028**	0.023
	(0.041)	(0.035)	(0.014)	(0.015)
Panel B: Normalized enforcement index				
Enforcement	0.037	0.024	0.019**	0.015
	(0.028)	(0.024)	(0.009)	(0.010)
Control variables	No	Yes	No	Yes
Exporter fixed effects	No	Yes	Yes	No
Year fixed effects	No	Yes	Yes	No
N	492	492	372	372

Outcome variables are the exports of corn (columns 1-2) and soybean (columns 3-4) from a U.S. state to the world in terms of the total monetary values in 2022 million U.S. dollars from the state-level USDA cash receipts estimates of exports. The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2 and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the baseline value of the total state-level exports. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 12: Placebo Test: Effects on International Import of Cereal Crops from Mexico and Canada

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Imports from Mexico				
Panel A1: Enforcement index				
Enforcement	0.267***	0.273	0.619***	0.458
	(0.019)	(0.227)	(0.063)	(0.712)
Panel A2: Normalized enforcement index				
Enforcement	0.186***	0.204	0.416***	0.334
	(0.012)	(0.149)	(0.037)	(0.447)
Panel B: Imports from Canada				
Panel B1: Enforcement index				
Enforcement	-0.078	-0.091	-0.127	-0.118
	(0.139)	(0.128)	(0.120)	(0.122)
Panel B2: Normalized enforcement index				
Enforcement	-0.050	-0.060	-0.140	-0.129
	(0.215)	(0.204)	(0.185)	(0.188)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
N	192	192	192	192

The outcome variables are the imports for a U.S. state from either Mexico or Canada in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A1 and B1, is the summation index created in equation (21). The explanatory variable for Panel A2 and B2 is the summation index is the normalized version of the summation index. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 13: Effects on Interstate Export of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Police-based Enforcement	-0.170**		-0.185**	
	(0.081)		(0.091)	
Employment-based Enforcement	-0.070		-0.101	
	(0.185)		(0.204)	
287g County		-0.416		1.373
		(1.823)		(1.748)
287g State		-0.112		-0.349**
		(0.152)		(0.170)
E-Verify		-0.003		-0.078
		(0.195)		(0.196)
Secure Communities		0.027		0.699**
		(0.220)		(0.301)
Omnibus Bill		-0.356**		-0.397**
		(0.177)		(0.173)
Control variables	Yes	Yes	Yes	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Importer-by-year fixed effects	Yes	Yes	Yes	Yes
N	8,392	8,392	8,500	8,500

The outcome variables are the exports from a U.S. state to other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with importer-year fixed effects and importer-exporter fixed effects, and state controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 14: Effects on Interstate Import of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Police-based Enforcement	0.237***		0.308**	
	(0.087)		(0.122)	
Employment-based Enforcement	-0.156		-0.408	
	(0.210)		(0.259)	
287g County		-1.296		-1.589
		(0.907)		(1.167)
287g State		0.233		0.069
		(0.161)		(0.231)
E-Verify		-0.146		-0.433
		(0.230)		(0.277)
Secure Communities		0.078		0.458
		(0.228)		(0.305)
Omnibus Bill		0.325*		0.558***
		(0.167)		(0.213)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Exporter-by-year fixed effects	Yes	Yes	Yes	Yes
N	8,392	8,392	8,500	8,500

The outcome variables are the exports from a U.S. state to other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, and state controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 15: Effects of Economic Variables on the First Adoption of Immigration Enforcement Program

	2002 Values			2002 - 1997 Values		
	(1)	(2)	(3)	(4)	(5)	(6)
Exports (in dollars)	0.000		0.001	-0.000		-0.000
	(0.000)		(0.001)	(0.000)		(0.001)
Bartik-style measure		-38.155	-35.942		-38.155	-41.370
		(32.203)	(34.602)		(32.203)	(36.204)
Minimum wage			0.300			0.273
			(0.528)			(0.547)
Adverse Effect Wage Rate			1.177			-0.831
			(1.044)			(1.440)
Housing Price Index			-0.006			0.011
			(0.019)			(0.025)
N	48	48	48	48	48	48

Outcome variables are the exports from a U.S. state to other U.S. states in terms of the total monetary values of vegetables in 2023 million U.S. dollars (columns 1-3) and the total weight in thousand tons (columns 4-6) from the USA Trade Online data administered by the U.S. Census Bureau. The primary explanatory variable, Enforcement, for Panel A, is the summary index using the standardized inverse covariance weighted average of pre-treatment agricultural-acreage-weighted shares of the exporter state that experienced each of the five immigration enforcement policies. The primary explanatory variable for Panel B is the summation index created in equation (21). Regressions in columns (1) and (4) use the Ordinary Least Squares model without any controls and fixed effects. Those for columns (2) and (5) use the Poisson Pseudo-Maximum Likelihood (PPML) estimator with destination-year fixed effects and importer-by-exporter pair fixed effects but no state-level controls. Those for columns (3) and (6) control for logged agricultural GDP of the exporter, state-level Adverse Effect Wage Rate, state-level seasonal-adjusted Housing Price Index, the Bartik-style control of labor demand shocks, and use the destination-year fixed effects and importer-by-exporter pair fixed effects. The pre-treatment mean shows the mean of the outcome variable from 1997 and 2002 combined. All regressions are weighted by the logarithmic function of the product of the GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Table 16: Effects on International Exports of Fruits and Vegetables

	Monetary Value		Weight	
	(1)	(2)	(3)	(4)
Panel A: Summary index				
Enforcement	-0.403*	-0.380*	-0.688**	-0.543**
	(0.230)	(0.200)	(0.304)	(0.261)
Panel B: Normalized summary index				
Enforcement	-0.315*	-0.297*	-0.538**	-0.426**
	(0.180)	(0.157)	(0.238)	(0.205)
Control variables	No	Yes	No	Yes
Importer-exporter pair fixed effects	Yes	Yes	Yes	Yes
Importer-by-year fixed effects	Yes	Yes	Yes	Yes
N	1524	1524	1528	1528

The outcome variables are the imports from a U.S. state to other U.S. states in terms of the total monetary values of fruits and vegetables in 2023 million U.S. dollars (columns 1-2) and the total weight in thousand tons (columns 4-6) from the Freight Analysis Framework (FAF-5). The explanatory variable, Enforcement, for Panel A, is the summation index created in equation (21). The explanatory variable for Panel B is the summation index is the normalized version of the summation index. High Exporter Enforcement is a binary dummy variable that equals 1 if the highest enforcement intensity at the state level (in 2012) for the exporter state is above the median value. All regressions use the reduced-form gravity model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator with exporter-year fixed effects and importer-exporter fixed effects, however, only regressions from columns (2) and (4) use the controls, the Bartik-style controls and the weighted state-level weather controls. All regressions are weighted by the logarithmic function of the product of the agricultural GDPs of importer and exporter states divided by the distance between their centroids. Robust standard errors clustered at the origin-by-destination level. *** 0.01, ** 0.05, * 0.1.

Appendices

A Appendix: Tables and Figures

B Appendix: Derivation of $\mathbf{c}_{ij}$

I begin by considering a consumer in region j, who maximizes utility based on a Constant Elasticity of Substitution (CES) utility function. The utility function, which represents the preferences of the consumer, is given by:

$$U_j = \left(\sum_i \alpha_i^{\frac{1}{1-\sigma}} \cdot c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{30}$$

where c_{ij} denotes the consumption of goods from region i by consumers in region j. The parameter α_i is a positive distribution parameter, and σ is the elasticity of substitution between goods from different regions.

The consumer maximizes utility subject to a budget constraint, which is expressed as:

$$\sum_i p_{ij} \cdot c_{ij} = y_j. \tag{31}$$

Here, p_{ij} is the price of goods from region i in region j, and y_j represents the nominal income of region j. The consumer allocates their income across different goods, taking into account the prices and their preferences for goods from different regions.

To solve this utility maximization problem, I use the method of Lagrange multipliers. The Lagrangian for the problem is formulated as follows:

$$\mathcal{L} = \left(\sum_i \alpha_i^{\frac{1}{1-\sigma}} \cdot c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \lambda \left(\sum_i p_{ij} \cdot c_{ij} - y_j \right), \tag{32}$$

where λ is the Lagrange multiplier associated with the budget constraint.

Next, I derive the first-order conditions by taking the partial derivative of the Lagrangian with respect to each consumption quantity c_{ij}, and setting it equal to zero. This yields the following condition:

$$\frac{\partial \mathcal{L}}{\partial c_{ij}} = \frac{\sigma}{\sigma - 1} \cdot \alpha_i^{\frac{1}{1-\sigma}} \cdot c_{ij}^{\frac{-1}{\sigma}} \cdot \left(\sum_i \alpha_i^{\frac{1}{1-\sigma}} \cdot c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} - \lambda \cdot p_{ij} = 0. \tag{33}$$

Simplifying this expression leads to:

$$\frac{\sigma}{\sigma - 1} \cdot \alpha_i^{\frac{1}{1-\sigma}} \cdot c_{ij}^{\frac{-1}{\sigma}} \cdot U_j^{\frac{1}{\sigma}} = \lambda \cdot p_{ij}. \tag{34}$$

I can solve this equation for c_{ij}, which gives the demand for goods from region i by consumers in region j:

$$c_{ij} = \left(\frac{\frac{\sigma}{\sigma-1} \cdot \alpha_i^{\frac{1}{1-\sigma}} \cdot U_j^{\frac{1}{\sigma}}}{\lambda \cdot p_{ij}} \right)^{\sigma}. \tag{35}$$

To determine the value of the Lagrange multiplier λ, I substitute this expression for c_{ij} into the budget constraint:

$$\sum_i p_{ij} \cdot \left(\frac{\frac{\sigma}{\sigma-1} \cdot \alpha_i^{\frac{1}{1-\sigma}} \cdot U_j^{\frac{1}{\sigma}}}{\lambda \cdot p_{ij}} \right)^{\sigma} = y_j. \tag{36}$$

This simplifies to:

$$\sum_i \left(\frac{\frac{\sigma}{\sigma-1} \cdot \alpha_i^{\frac{1}{1-\sigma}} \cdot U_j^{\frac{1}{\sigma}}}{\lambda} \right)^{\sigma} = y_j. \tag{37}$$

I can factor out the common terms from the summation:

$$\left(\frac{\frac{\sigma}{\sigma-1} \cdot U_j^{\frac{1}{\sigma}}}{\lambda} \right)^{\sigma} \cdot \sum_i \alpha_i^{\frac{\sigma}{1-\sigma}} = y_j. \tag{38}$$

Now, solving for λ, I obtain:

$$\lambda^{\sigma} = \left(\frac{\sigma}{\sigma-1} \right)^{\sigma} \cdot U_j \cdot \frac{1}{y_j} \cdot \sum_i \alpha_i^{\frac{\sigma}{1-\sigma}}. \tag{39}$$

Taking the σ-th root on both sides gives:

$$\lambda = \frac{\sigma}{\sigma-1} \cdot \left(\frac{U_j}{y_j} \cdot \sum_i \alpha_i^{\frac{\sigma}{1-\sigma}} \right)^{\frac{1}{\sigma}}. \tag{40}$$

Finally, substituting the expression for λ back into the demand function c_{ij}, I get:

$$c_{ij} = \left(\frac{\frac{\sigma}{\sigma-1} \cdot \alpha_i^{\frac{1}{1-\sigma}} \cdot U_j^{\frac{1}{\sigma}}}{\frac{\sigma}{\sigma-1} \cdot \left(\frac{U_j}{y_j} \cdot \sum_i \alpha_i^{\frac{\sigma}{1-\sigma}} \right)^{\frac{1}{\sigma}} \cdot p_{ij}} \right)^{\sigma}. \tag{41}$$

This simplifies further to:

$$c_{ij} = \left(\frac{\alpha_i^{\frac{1}{1-\sigma}} \cdot y_j}{p_{ij} \cdot \sum_i \alpha_i^{\frac{\sigma}{1-\sigma}}} \right)^{\sigma}. \tag{42}$$

Recognizing that the term $\sum_i \alpha_i^{\frac{\sigma}{1-\sigma}}$ can be interpreted as part of the CES price index P_j, I introduce the CES price index:

$$P_j = \left(\sum_i \alpha_i \cdot p_{ij}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{43}$$

Therefore, the final expression for the demand function is:

$$c_{ij} = \alpha_i \cdot \left(\frac{p_{ij}}{P_j} \right)^{-\sigma} \cdot \frac{y_j}{p_{ij}}. \tag{44}$$

This demand function reflects the consumption of goods from region i by consumers in region j, and it depends on the price of goods from region i relative to the overall price index in region j, adjusted for the elasticity of substitution σ and the distribution parameter α_i.