

Immigrants, Legal Status, and Illegal Trade

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Abstract

Nearly \$2 trillion of illegally trafficked goods flow across international borders every year, generating violence and other social costs along the way. Some have controversially linked illegal trafficking to immigrants, especially immigrants without legal status. In this paper, I use novel data on nearly 10,000 confiscations of illegal drugs in Spain to study how immigrants and immigration policy affect the pattern and scale of illegal drug trafficking. To identify the causal effect of immigrants on trafficking, I construct an instrumental variable that interacts variation in total immigrant inflows into Spain across origin countries with the fraction of immigrants inflowing into a province. I find that a 10% increase in the population of immigrants from a given origin country relative to the mean raises the likelihood of illegal importing drugs from that origin country by 0.8 percentage points. Moreover, immigrants without legal status drive illegal drug imports, while authorized immigrants drive exports. To better understand the role of legal status, I exploit an extraordinary regularization of nearly half a million immigrants in 2005. Event study estimates suggest that granting immigrants legal status results in a decline in drug imports.

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1 Introduction

Many illegal goods are not produced where they are consumed, resulting in the trafficking of nearly \$2 trillion of illegal goods across international borders annually, worth 10% of the value of legal global merchandise trade (Mavrellis, 2017). Violence often follows in the wake of illegal trafficking, and further costs to society occur when the illegally trafficked goods—particularly illegal drugs—are consumed (NDIC, 2011). This illegal trafficking often relies on informal connections and social ties to facilitate the movement of goods without binding contracts (Marsh et al., 2012).

One controversial but untested opinion holds that immigrants, particularly those without legal status, facilitate the trafficking of illegal goods from their origin country to their host region.¹ Immigrants’ social connections to their origin country may make arranging for imports and exports (legal or illegal) easier (Rauch and Trindade, 2002; Combes et al., 2005; Dunlevy, 2006). In addition, immigrants without legal status are prevented from working in the formal sector, thereby reducing their earnings relative to their legal counterparts (Kossoudji and Cobb-Clark, 2002; Kaushal, 2006; Simón et al., 2014; Sanromá et al., 2015). The Becker-Ehrlich model of crime (Becker, 1968; Ehrlich, 1973) suggests that this differential in earnings will result in a higher propensity to participate in financially motivated illegal activities, such as trafficking illegal goods.

In this paper, I estimate how immigrants and immigration policy affect the trafficking of one of the most consequential illegal goods: illicit drugs. I use novel data on drug confiscations from Spain and exogenous variation in immigrant populations to show that immigrants have a large, positive causal effect on the trafficking of illegal drugs with immigrants’ countries of origin. I also find that immigrants’ legal status is a crucial determinant of drug trafficking, with irregular immigrants raising illegal imports and regular immigrants raising illegal exports. Because immigrants may select into a legal status and into participation in drug trafficking due to unobserved characteristics, I estimate the effects of a mass immigrant regularization policy. I find that granting immigrants legal status results in a decline in illegal drug imports, with no effect on exports.

The main contribution of this paper is to provide the first causally identified estimates of

¹Several notable politicians have made this claim. Donald Trump suggested in 2015 that Mexican immigrants were “bringing drugs [and] crime” into the United States. Then-presidential candidate Sebastian Piñera in 2017 blamed Chile’s immigration laws for “importing problems like delinquency, drug trafficking and organized crime” (Esposito and Iturrieta, 2017). In addition, the European Union High Representative for Common Foreign and Security Policy argued in 2003 that, “massive flow[s] of drugs and migrants are coming to Europe and [will] affect its security. These threats are significant by themselves, but it is their combination that constitutes a radical challenge to our security” (Solana, 2003). More broadly, in both the United States and European rounds of the Transatlantic Trends survey, respondents blame irregular immigrants for increasing crime much more than they blame regular immigrants.

the effect of immigrants on illegal trafficking and the first exploration of the mechanisms that generate this relationship. Credibly establishing a causal relationship between immigrants without legal status and drug trafficking is challenging for two reasons. First, the illegal nature of trafficking and undocumented immigration makes measurement of these two phenomena difficult. Second, other factors (such as geography) may affect both the distribution of immigrant populations and illegal drug trafficking.

To make progress on the difficulty in measuring illegal drug trafficking, I use detailed data on drug confiscations that include information on which country the drugs were trafficked from. In particular, I use a database of individual drug confiscations as a proxy for actual drug flows in the context of Spain, a country with high-quality reporting of data on drug confiscations. These data report where the drug confiscation occurred within Spain, from which country the drugs were trafficked, and, if available, to which country the drugs were intended to be trafficked, thus providing insight into the region-to-region flows of illegal drugs. To validate that this indirect measure captures variation in actual flows of illegal goods, I compare confiscations to survey-based measures of drug use and availability at the province level. I find that more confiscations correspond to more drug use and availability.

Spain provides a unique context to study whether and how immigrants and immigrant legal status affect the flow of illegal drugs. Spain is a major hub for cocaine and cannabis trafficking into Europe. The country has also experienced substantial immigration in recent decades, much of it unauthorized.

I exploit unique institutional features in Spain that facilitate the measurement of irregular immigrant populations. Unlike the United States and many other European countries, immigrants to Spain can obtain healthcare and other government benefits regardless of their legal status in exchange for enrolling in their local population registry. Comparing local population registries with counts of permits for legal residency leads to a straightforward estimation of the size of the irregular immigrant population ([González-Enríquez, 2009](#); [Gálvez Iniesta, 2020](#)).

To make progress on causal identification, I estimate a gravity equation, the workhorse model in the international trade literature used to explain the volume of trade flowing from one region to another ([Tinbergen, 1962](#); [Head and Mayer, 2014](#)). I estimate a gravity equation of illegal drug trafficking, relating the likelihood or value of drug trafficking between a foreign country and Spanish province with the number of immigrants from that country living in the province. Because I observe origins and destinations of both drugs and immigrants, I can flexibly control for observed and unobservable features of each country and each Spanish province using country and province fixed effects. These fixed effects absorb variation in law enforcement activity directed towards specific nationalities in Spain (as with the country

fixed effect) and variation in law enforcement efficacy in confiscating drugs across provinces (as with the province fixed effect).

There may still be factors at the country-province pair level that drive both drug trafficking and immigration from the country to the province. For example, Moroccan immigrants and Moroccan drug traffickers may be drawn to Barcelona for its familiar Mediterranean climate. To address this potential endogeneity, I adapt the instrumental variables approach developed by [Burchardi et al. \(2019\)](#) to generate exogenous variation in the number of immigrants from a given country living in a given Spanish province. The instrument relies on the intuition that immigrants from origin country o are likely to settle in Spanish province d if many immigrants from o are arriving in Spain at the same time that many immigrants are settling in d . In particular, the instrument interacts the “pull” of Spanish province d to immigrants—measured as the share of immigrants in a given decade settling in d —with the “push” to immigrate from origin country o —measured as the number of immigrants from o entering Spain in a given decade.

I find that a higher immigrant population from a given origin country facilitates the import and export of illegal drugs from that origin country. For an average Spanish province, I find that a 10% increase in the number of immigrants relative to the mean from a given origin country raises the likelihood that illegal drugs trafficked from that origin country will be confiscated locally by 0.8 percentage points. Similarly, a 10% increase in the number of immigrants relative to the mean from a given origin country raises the likelihood that drugs intended for export to the immigrants’ origin country will be confiscated locally by 0.3 percentage points.

These main results are robust to a range of alternative specifications and sampling choices. No single drug variety or region drives my baseline result, as I find consistent effects when leaving out individual origins, destinations, and drugs. In addition, I find that immigrants also raise the value of illegal drug imports and exports. Finally, my results also hold when estimating a yearly panel of drug confiscations and immigrant populations.

Immigrants’ social connections to their origin country primarily drive the bilateral immigrant-trafficking relationship that I estimate. I argue that my quantitative evidence is consistent with the qualitative evidence that immigrants reduce information frictions and transaction costs for illegal imports and exports. In addition, I find that immigrants raise exports of drugs, a margin where immigrants’ demand for drugs does not have an effect. An alternative explanation is that immigrants may prefer to consume goods from their home country ([Bronnenberg et al., 2012](#); [Atkin, 2013](#)). However, product differentiation of illegal drugs across trafficking origins is unlikely to occur in the context of drug markets. In addition, I find that immigrants consume drugs at significantly lower rates than native-born Spaniards,

and immigrants raise exports at similar magnitudes as they raise imports.

A competing explanation for my baseline results is that the intensity with which law enforcement conducts drug enforcement activities is affected by the size of the local immigrant population. Due to the country and province fixed effects in my baseline specification, such law enforcement intensity must disproportionately affect country-province pairs with more immigrants. In my baseline estimation, I assume that enforcement intensity does not co-vary with the immigrant population at the country-province pair level. I indirectly test this assumption by focusing on country-province pairs that I predict to be on the margin of trafficking drugs. I find a large positive effect of immigrants on confiscations at the extensive margin of trafficking, suggesting that enforcement intensity cannot fully explain my baseline results.

I also find that general equilibrium responses, including changes in the participation of the native-born in drug markets, cannot fully explain the estimated relationship between immigrants and trafficking. I assess the strength of these general equilibrium responses by estimating the effect of immigrants on measures of drug market activity at the province level. I find that an increase in the immigrant population in a province (across all origin countries) raises the value of drugs confiscated locally.

To understand the role of immigration policy, I estimate the effect of immigrants on drug trafficking separately by immigrant legal status using the gravity specification. I find that my baseline estimates for imports are driven entirely by irregular immigrants; however, regular immigrants drive the effect for exports. I argue that the differing effects of legal status on imports and exports result from specific institutional features of the European Union, whereby exporting into the E.U. from Spain is necessarily done by immigrants with legal status. In contrast, irregular immigrants are more likely to import drugs into Spain following the standard logic of Becker's model of crime.

To achieve causal identification in the effect of immigrants by legal status on trafficking, I interact the leave-out push-pull instrument from the baseline estimation with a predicted propensity for immigrant irregularity at the origin country-province level. I predict irregularity for a country-province pair in 2011 using the lagged share of immigrants from the country and outside the region of the province.

Unobserved immigrant characteristics, such as a propensity for illegal behavior, may drive immigrants into irregularity and drug trafficking. These differences in the composition of immigrants by legal status at the country-province level may partly explain my instrumented gravity estimates. To better understand the effects of legal status on trafficking, I exploit a major immigrant regularization program implemented in 2005. This program resulted in nearly half a million immigrants receiving legal status.

I find that the 2005 mass immigrant regularization reduced the likelihood of illegal drug importation significantly. For example, I estimate that legalizing 10% of the irregular immigrant population from a given origin country would reduce the likelihood of illegal drug imports from that country by 1.4 percentage points.

This paper provides the first causally identified estimates of the effect of immigrants and immigrant legal status on illegal trafficking. Related work by [Berlusconi et al. \(2017\)](#), [Giommoni et al. \(2017\)](#), and [Aziani et al. \(2019\)](#) uses country-pair level data on drug confiscations to assess how immigrant population at the country-pair level correlates with drug confiscations. I make four main advancements relative to this literature. First, I use credibly exogenous variation in bilateral immigrant population. Second, I include origin and destination fixed effects to control for observed and unobserved factors at the region-level that shape immigration and trafficking. Third, I exploit within-country variation, which allows me to control country-pair level factors. Finally, I explore the underlying mechanisms that drive the observed immigrant-trafficking relationship and the resulting immigration policy implications.

This article contributes to the debate on the costs and benefits of immigration and on which immigration policies host countries should adopt. Much of the literature on the consequences of immigration has focused on labor market outcomes.² A separate literature has estimated the effect of immigrants on legal trade ([Gould, 1994](#); [Head and Ries, 1998](#); [Rauch and Trindade, 2002](#); [Combes et al., 2005](#); [Cohen et al., 2017](#); [Parsons and Vézina, 2018](#)). This paper expands upon this literature by looking at a new outcome—illegal trade—changing as a result of immigration and by showing that the legal status regime of the host country is crucial for shaping this relationship.

My work complements existing studies on the effect of immigrants on crime. I provide evidence for a new mechanism linking immigration and crime: immigrants’ social connections to their home country. Prior research on immigration and crime tends to focus on the labor market opportunities available to immigrants ([Bell et al., 2013](#); [Spenkuch, 2014](#); [Pinotti, 2017](#); [Freedman et al., 2018](#)). I complement recent work by [Stuart and Taylor \(2021\)](#) on how social connectedness affects crime by highlighting a context in which social connections can increase, rather than decrease, the propensity to commit crime.

I also expand upon the literature on the economics of illegal trade by studying the trafficking of illicit drugs, one of the most consequential of illegally smuggled goods.³ Following

²See, for example, [Card \(2001\)](#), [Friedberg \(2001\)](#), [Borjas \(2003\)](#), [Dustmann et al. \(2013\)](#), and [Monras \(2020\)](#). For a recent review of the literature, see [Dustmann et al. \(2016\)](#).

³A key distinction between past studies on the economics of drug trafficking and the present paper is that I look at *bilateral*, rather than region-specific, determinants of drug trafficking. Other studies have looked at the consequences of law enforcement crackdowns on drug cultivation ([Abadie et al., 2014](#); [Mejía et al.,](#)

a strand of mostly theoretical papers on the economics of smuggling (Bhagwati and Hansen, 1973; Grossman and Shapiro, 1988; Thursby et al., 1991), more recent empirical work by Fisman and Wei (2009) and Akee et al. (2014) studies the smuggling of cultural goods, and the determinants of human trafficking, respectively.

This paper proceeds as follows. Section 2 introduces the data and validates the drug confiscations data as a proxy for actual drug flows. Section 3 presents my empirical strategy and results. In section 4 I rule out enforcement intensity and general equilibrium responses explaining my baseline results, and in Section 5 I discuss the role of immigrant legal status. Section 6 concludes.

2 Background and Measurement of Drug Trafficking

2.1 Background

Illegal Drugs. The most commonly consumed illegal drugs around the world are cannabis, opioids, amphetamines and prescription stimulants, ecstasy, and cocaine, ranked by number of users in 2018 (p.7, UNODC, 2020b). Cannabis and cocaine are the primary drugs trafficked in Spain. The country serves as an key entry point to Europe for these drugs.⁴

Illegal drugs typically pass through many countries between their production location and final consumption location. Cocaine, for example, is grown exclusively in three countries in the world: Colombia, Peru, and Bolivia. While the United States and Europe represent the primary consumption regions in the world, cocaine passes through intermediary countries such as Mexico or West Africa on the way to these markets.⁵

Cannabis, by contrast, “is produced in almost all countries worldwide.”⁶ Nevertheless, a large amount of cannabis is still trafficked across international borders, although it tends to remain in the same region.⁷

In Spain, confiscations of domestic cannabis plants (Alvarez et al., 2016) are quite small compared to the amount of cannabis confiscated arriving from abroad. Amphetamines can also be produced locally, but are a small part of the market, with only 2% of drug treatment patients seeking help for an amphetamine addiction. This fraction is roughly in line with 2017) and violence (Castillo et al., 2020). A notable exception is Dell (2015), who estimates how crackdowns shape violence and drug trafficking networks. However, Dell (2015) lacks data on the bilateral flows of illegal drugs.

⁴See https://www.emcdda.europa.eu/countries/drug-reports/2019/spain/drug-markets_en.

⁵UNODC (p. 30, 2020a).

⁶UNODC (p. 67, 2020a).

⁷UNODC (p. 71-73, 2020a).

the share of amphetamines in total confiscations.⁸

Due to the intermediary-intensive nature of trafficking, social connections between countries may facilitate trafficking routes. For example, in a set of interviews in the United Kingdom conducted by [Matrix Knowledge Group \(2007\)](#), jailed traffickers shared the importance of social ties. Most recruiting of workers in the drug trafficking business occurred within one’s social network⁹, and traffickers also noted examples in which a shared nationality raised trust between individuals seeking to conduct illegal trade transactions.¹⁰ Proximity to immigrants from a variety of drug source countries was seen as advantageous as it reduced search costs.¹¹ In the context of legal trade, [Rauch and Trindade \(2002\)](#) note that punishment of cheating firms within a migrant network can facilitate trade given incomplete contracts, which bear particular relevance for the case of illegal transactions.

Immigration. Spain has experienced tremendous immigration in recent decades. Between 1991 and 2011, the share of immigrants in Spain’s population rose from below 1% to well over 10% as shown in Figure 9, representing “the highest rate of growth of the foreign-born population over a short period observed in any OECD country since the Second World War” ([OECD, 2010](#)).

Immigrants without legal status, or irregular immigrants, are a common feature of immigration in Spain. Irregular immigrants are defined as those living in the country without a residency permit, and they generally enter Spain through legal means ([González-Enríquez, 2009](#)). These include immigrants who overstay their tourist visas and stay in Spain beyond the terms of their temporary residence permits.¹² Moreover, irregular immigration is a common phenomenon in Spain among immigrants. Surveys of immigrants in Spain have found that nearly 50% of immigrants are irregular ([Pajares, 2004](#); [Yruela and Rinken 2005](#)). [Díez Nicolás and Ramírez Lafita \(2001\)](#) found that 83% of immigrants had arrived in Spain without a work permit but nevertheless began to work or look for a job.

Concurrent with its high levels of immigrant irregularity has been Spain’s relatively more generous provision of public services to irregular immigrants as well as providing a path to

⁸See <https://www.emcdda.europa.eu/countries/drug-reports/2019/spain-en>.

⁹“A number of interviewees indicated that the importance of trust meant that they only recruited employees [for their smuggling organization] largely through their existing social networks.” ([Marsh et al., 2012](#))

¹⁰For example, “[One convicted drug trafficker] was from Ghana. In 2000 he was approached by a Ghanaian friend to manage his drug business in the United Kingdom. He was trusted by the dealers he had to manage because they knew his family in Ghana.” ([Marsh et al., 2012](#))

¹¹For example, one convicted trafficker said that to import cocaine into the United Kingdom, “You need to know someone in the West Indies but this is not difficult to do. London is multicultural, you can meet a contact.” [Matrix Knowledge Group \(2007\)](#)

¹²Irregular immigrants who enter Spain via either crossing the Strait of Gibraltar by boat or by illegally entering the Spanish North African cities of Ceuta or Mellila are a small fraction of irregular immigrants, though they garner a disproportionate share of press coverage ([González-Enríquez, 2009](#)).

regular status and thereafter to citizenship. For example, the country regularly provided legal status to hundreds of thousands of irregular immigrants in waves of regularizations between 2000 and 2005. In addition, irregular immigrants are eligible for access to the country’s public healthcare and education systems so long as they register with the local population registry. These benefits create a strong incentive for irregular immigrants to register, a fact that I leverage to measure irregular migration prevalence in Section 5.1.¹³

Obtaining legal status puts immigrants on the path to citizenship. Immigrants must live in Spain continuously and legally for ten years before they can apply for naturalization. For immigrants from Latin America, this requirement drops to two years. In addition, immigrants must meet various assimilation and “good citizen” requirements, such as Spanish language fluency and not committing crimes.

2.2 Drug Trafficking Data Description

Data limitations typically complicate the study of illegal activity. In the context of drug trafficking, I use data on confiscations of illegal drugs by law enforcement to proxy for actual illegal drug flows. To validate that drug confiscations capture variation in actual flows of illegal goods, I compare confiscations to survey-based measures of drug availability and use them at the province level.

I use a database of individual drug confiscation events to proxy for actual drug flows in the context of Spain, a country with high-quality reporting of drug confiscations. Using enforcement-based measures as a proxy for illegal and therefore hard-to-observe activity is typical in the study of crime. For example, Dell (2015) uses confiscations of illegal drugs in a region as a proxy for the amount of illegal drugs flowing through the region.¹⁴ Similarly, Dube et al. (2016) uses the number of opium poppy and cannabis plants eradicated as a proxy for cultivation.

I measure drug confiscations using a novel dataset of individual wholesale-level confiscations events compiled by the United Nations Office of Drugs and Crime (UNODC). An observation in these data is a single drug confiscation event and details the drug type, the amount confiscated, the country from which the drugs were trafficked, and the location of the

¹³The population registry is an imperfect measure for several reasons. First, municipalities differ in their documentation requirements for registration and the degree to which they notify immigrants that they must re-register every two years. In addition, according to González-Enríquez (2009), sex workers and immigrants from China are less likely to register due to deportation fears. This will impact my estimation strategy only if there is a bilateral-specific measurement error term, so origin country-specific immigrant behaviors common across all provinces, or destination province policies common across all origins will be controlled for by the origin and destination fixed effects.

¹⁴Whereas my data on drug confiscations are at the bilateral (region-to-region) level, Dell (2015) uses confiscations aggregated to the region-level.

confiscation. By including both the locality of a confiscation and its country of departure, I observe the bilateral linkage for each confiscation event. A subset of confiscations lists the intended destination country of the confiscated drugs. To transform quantities confiscated in dollar amounts, I use illegal drug prices reported by the Centre of Intelligence against Organized Crime at the Spanish Ministry of the Interior.¹⁵

I primarily use confiscations reported by Spain due to their high quality.¹⁶ These data are compiled in Spain’s Statistical System of Analysis and Evaluation on Organized Crime and Drugs, a centralized repository of information on organized crime and the illegal drug trade. This database is filled out by three national law enforcement agencies: the National Police, the Guardia Civil, and the Customs and Excise Department. These agencies report both confiscations made by their own personnel as well as by those conducted in concert with, or exclusively by, local law enforcement authorities.

Country of origin and intended destination for each drug confiscation in the dataset is assigned based on subsequent investigation, where country of origin refers to the most recent foreign country the drugs had been in (not necessarily the country in which they were produced). For some drug interdictions, assignment of origin and destination country is fairly straightforward. For drugs confiscated from airline passengers upon arrival at an airport, the origin country is the passenger’s departure country and destination country is the passenger’s ultimate destination on their travel itinerary. For drugs confiscated from cargo ship containers, a range of documents are checked for country of origin and intended destination, including the bill of lading, the commercial invoice, the certificate of origin, customs clearance forms, and the relevant letter of credit. In the case of “narco-boats” that transport hashish resin in the Strait of Gibraltar, their country of origin is considered to be Morocco unless proven otherwise.

For less straightforward cases, such as the case of drug gangs transporting cocaine intercepted in the Atlantic Ocean off the Galician coast, the country of origin and destination is determined based on additional information such as suspect and witness interviews and coordination with law enforcement agencies in the suspected origin and destination countries. If a person is arrested within Spain for drug trafficking but is outside an airport or port, the

¹⁵Specifically, these are prices in dollars for 2012 for heroin, cocaine, amphetamines, and cannabis as reported by Spain to the UNODC. I assume prices are uniform across origins and destinations.

¹⁶Reporting drug confiscations to the UNODC is voluntary. I focus on Spain, a country that reports a large number of drug confiscations to the UNODC annually (see Figure 8) and reports substantially higher quality data than other countries. For example, Spain reports at high rates fields typically missing from reports by other countries, such as the hiding place of confiscated drugs, the installation where law enforcement found the drugs, the mode of transport, and the routing of the drugs. Between 2011 and 2016, confiscation events from Spain were missing these fields for only 20% of events, while the fraction of these variables missing rose to 33% when turning to other countries. In the same time period, Spain reported the highest number of confiscations of any country.

country of origin of the drugs will be determined on the basis of the investigation carried out, including any statements made by the arrested person. ¹⁷

Four facts emerge when looking at the data on confiscations in Spain. First, nearly all drugs confiscated by Spanish authorities are cocaine or cannabis, with negligible amounts of amphetamines and heroin as shown in Figure 10. Second, the distribution of drug confiscation amounts is right skewed as shown in Figure 11, with many moderate-sized confiscations (the median confiscation value is \$43,796) and a few huge confiscations (the mean confiscation value is \$593,795). Third, Spain imports cannabis almost exclusively from Morocco and cocaine from Latin America, as shown in Figure 12, and Spain exports drugs primarily to the rest of Europe and the Mediterranean region. Finally, there is substantial spatial variation across Spain of the import and export of illegal drugs, as shown in Figures 14 and 15.

2.3 Validation Exercise

In this section I demonstrate that the drug confiscations data are a valid proxy for actual illicit drug flows. In particular, I correlate confiscations of imported drugs per capita (net of confiscations destined for other countries) in a locality to the availability of drugs in that locality. This approach is valid if local production is small relative to the local market, an assumption likely to hold in Spain as discussed in Section 2.1.

To measure local drug availability, I turn to the Survey on Alcohol and Drugs in Spain (EDADES). The EDADES is a nationally representative biennial survey on substance use in Spain, interviewing 20,000 to 30,000 persons per survey. Respondents are asked how easy it is for them to access various illegal drugs within 24 hours, how much of a problem illegal drugs are in their neighborhood, and whether they have personally used various drugs. I aggregate responses across the 2011, 2013, and 2015 survey rounds to create a measure of province-level drug use and drug availability.

I find that confiscations of illegal drugs positively correlate with a wide range of measures of local drug availability. In Figure 1, I plot the correlation coefficient between reported ease or difficulty obtaining a particular drug within 24 hours and the amount of that drug that was confiscated in the province per capita between 2011 and 2016.¹⁸ Consistent with confiscations corresponding to real flows of illicit drugs, I find that when a higher proportion of respondents say it is “impossible” to obtain a particular drug, the amount of that drug

¹⁷The preceding description is based on discussions with representatives from the Spanish Ministry of the Interior.

¹⁸I do this exercise for cannabis, cocaine, and heroin, as respondents were not questioned about their access to amphetamines for the whole sample period. Respondents could reply that it was impossible, difficult, relatively easy, or easy to obtain the drug within 24 hours.

confiscated in the province is lower. Conversely, I find that the proportion of respondents saying it is “easy” or “very easy” to obtain a drug correlates positively with the amount of that drug confiscated in the province. This relationship is much stronger for cannabis and cocaine, the major drugs imported into Spain, and weaker for heroin, whose pathway into Europe is generally believed to lie through the Balkan countries rather than through Spain (UNODC, 2014).

I also find that confiscations are weakly correlated with respondents’ personal drug use history, as shown in Figure 16. I find a positive correlation between confiscations and personal use for cocaine, with imprecise zeros for cannabis and heroin.

In Figure 2 I plot the correlation coefficients of various measures of local drug availability and use to the value of confiscations per capita across all illicit drugs. I measure local drug availability and use as the fraction of respondents replying that (in the first bar of Figure 2) drugs are a major problem in their neighborhood or that (for the remaining bars) they frequently see evidence of drug use and distribution in their neighborhood. For each survey question, confiscations vary positively with local drug availability.¹⁹

Overall, these results suggest that confiscations by law enforcement are a valid proxy for actual flows of illicit drugs. They are also consistent with Dobkin and Nicosia (2009), who find that drug markets quickly rebound even in response to confiscations of massive quantities of drugs.

3 Bilateral Empirical Analysis

I seek to understand whether immigrants facilitate drug trafficking between their origin country and their new home province. To do so, I relate drugs coming from a given origin country and confiscated locally with a measure of the number of immigrants from that origin country and living locally. Exploiting this country-province-pair level variation, I can flexibly control for observed and unobserved characteristics of the country and the province. Because migration and drug trafficking may be jointly determined by other factors, such as geographic or climatic similarity between country and province, I generate exogenous variation in the immigrant population using an instrumental variables strategy.

¹⁹Respondents are asked how often in their neighborhood they see people (i) drugged and on the ground, (ii) inhaling drugs in paper or aluminium, (iii) injecting drugs, (iv) selling drugs, (v) smoking joints, (vi) snorting drugs by nose, and (vii) leaving syringes lying on the ground.

3.1 Preliminary Evidence

There exists a positive correlation between the number of immigrants and the value of drugs confiscated at the country-province level, as shown in Figure 17. This relationship may be driven by other factors, such as origin- or destination-specific institutions (e.g., economic development) or by country-province-pair factors such as geographic similarity. For example, consider the case of Morocco, a major source of both immigrants and cannabis flowing into Spain. Spatially, there is substantial overlap between the immigrant population and the location of confiscations of cannabis coming from Morocco (often on Spain’s southern and eastern coast), as shown in Figure 3.

A natural explanation for this correlation is that geographic distance—since Morocco is directly to the south of Spain—drives both trafficking and immigration from Morocco and into southern Spain. Other confounders, such as the similar climate enjoyed by much of Spain and Morocco may also explain this correlation. To more formally evaluate the relationship between immigrants and drug trafficking and rule out such confounders, I next estimate a gravity equation of drug confiscations in the context of Spain.

3.2 Gravity Regression

My bilateral empirical specification, the gravity equation, allows me to control for origin- and destination-specific characteristics that may shape trafficking and migration. This estimation strategy also allows me to deal with concerns about enforcement intensity variation driving observed drug confiscations.

Specification. I estimate a baseline gravity equation of the form

$$Y_{o,d} = \alpha_o + \alpha_d + \beta M_{o,d}^{2011} + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d} \quad (1)$$

where α_o and α_d are country and province fixed effects, respectively; $Y_{o,d}$ is either a dummy for any drug imports from o into d were confiscated ($\mathbf{1}[C_{o,d}^{2011-2016} > 0]$) or a dummy for any export from province d to country o were confiscated ($\mathbf{1}[C_{d,o}^{2011-2016} > 0]$); and $Dist_{o,d}$ is the distance in kilometers between o and d taken from Peri and Requena-Silvente (2010).²⁰ $M_{o,d}^{2011}$ is a measure of the number of immigrants from o living in d , defined as the log of one plus the number of immigrants in d from o , measured in thousands (however, my results are robust to alternative functional form choices, as I show in Section 3.9.1). The error term $\varepsilon_{o,d}$ includes all omitted bilateral forces that may shape drug trafficking. I measure the

²⁰I microfound the gravity equation in Appendix A.

immigrant population $M_{o,d}^{2011}$ using the 2011 Spanish Census distributed by the [Minnesota Population Center \(2019\)](#).

The origin country and destination province fixed effects are key to my identification strategy. The origin fixed effect α_o controls for, among other factors, the economic development, institutions, and crime in the origin country as well as national-level policies of Spain vis-a-vis origin country o . These country-pair level policies can include visa regimes, customs regulations, and national law enforcement priorities. Similarly, the destination fixed effect α_d controls for province d factors common across origins, such as province d 's police force strength and the economic conditions in d .

Thus β is identified off of variation in the drug confiscations and immigrant populations across country-province pairs. The identification assumption is that the country-province immigrant population $M_{o,d}^{2011}$ is independent of country-province-specific enforcement intensity $E_{o,d}$ and any other country-province-level confounder $\tilde{\epsilon}_{o,d}$.

I cluster standard errors at the origin country-level in my baseline specification, though my results are robust to alternative standard error clustering (see Table 12).

I estimate equation 1 separately for import confiscations and export confiscations. Looking at both import and export margins allows me better understand the mechanisms underlying any immigrant-trafficking relationship. For example, if immigrants raise exports then immigrant demand for drugs is unlikely to drive the relationship. To measure intended exports, I consider drugs confiscated in d but that were intended to go to country o .²¹

OLS Results. In Table 1, I show OLS estimates when iteratively adding fixed effects controls. As expected, I find that including the province and country fixed effects significantly reduces the strength of the positive correlation between immigrants and drug confiscations. These estimates demonstrate the importance of including country and province fixed effects to reduce omitted variable bias, suggesting prior studies ([Berlusconi et al., 2017](#); [Giommoni et al., 2017](#); [Aziani et al., 2019](#)) may overstate the role of immigrants in facilitating drug trafficking.

3.3 Instrumental Variables Approach

While country and province fixed effects absorb many potential confounders in by baseline specification, there may still be unobserved factors at the country-province-pair level, such as the geographic or climatic similarity between a foreign country and a Spanish province. Consider, for example, that Moroccan immigrants settling in the province of Barcelona

²¹Note that I primarily observe confiscations of drugs entering Spain, so this measure largely excludes any drugs domestically produced for export.

may be drawn to its similar Mediterranean climate. Additionally, drug traffickers skilled at piloting boats in the waters off the coast of Morocco may be skilled at piloting boats in similar climates, such as Barcelona’s.

To obtain variation in country-to-province-specific immigration that is exogenous to such concerns, I follow [Burchardi et al. \(2019\)](#) and develop a set of leave-out push-pull instruments for the number of immigrants arriving in a given region and coming from a given origin country. These instruments produce plausibly exogenous variation in bilateral immigrant inflows. I use two decades of inflows between 1991 and 2011 to predict the current number of immigrants from a given origin country living in a Spanish province.

The intuition of the instrument is that a social connection, in this case an immigration decision, between an origin and a destination is likely to occur when the origin is sending many immigrants at the same time the destination is pulling in many immigrants. For example, suppose we want to predict the number of Moroccans settling in the province of Barcelona. To do so, I look at the number of Moroccans inflowing into Spain and the number of immigrants from all origin countries inflowing into Barcelona for the same decade. In particular, the instrument will predict Moroccans to settle in Barcelona if large numbers of immigrants from other countries are also settling there. Similarly, if many immigrants from other origins are settling in Barcelona, then an immigrant arriving from Morocco will be predicted to settle in Barcelona.

Concretely, the migration leave-out push-pull instrument interacts the arrival into Spain of immigrants from different origin countries (push) with the attractiveness of different destinations to immigrants (pull) measured by the fraction of all immigrants to Spain who choose to settle in province d . A simple version of the instrument is defined as

$$\tilde{I}V_{o,d}^D = I_o^D \times \frac{I_d^D}{I^D}, \quad (2)$$

where I_o^D is the number of immigrants from origin o coming to Spain in decade D , and I_d^D/I^D is the fraction of immigrants to Spain who choose to settle in d . An inflow from o to d is defined as a person interviewed in d for the 2001 or 2011 Spanish census with a nationality from o who arrived in the 10 years prior to the survey.

Still, there may be threats to the exogeneity of the instrument as defined thus far. One potential exclusion restriction violation occurs when endogenous bilateral immigration is a large share of the instrument’s components. For example, if all Moroccan immigrants coming to Spain choose to settle in Barcelona due to its similar climate. A simple solution then it to leave out the bilateral immigration ($I_{o,d}^D$) when computing the instrument.

However, there might also be spatial correlation in confounding variables. For example,

both Moroccan and Algerian immigrants and drug traffickers may go to Barcelona for the same reason: a similar climate. Then, even leaving out Morocco-to-Barcelona immigration flows when computing the instrument is not sufficient, because now the Algerian immigration flows to Barcelona (used to predict Morocco-to-Barcelona flows) are contaminated with the confounding climate preference.

To avoid such endogeneity, I again follow [Burchardi et al. \(2019\)](#) and leave out both the continent of origin country o and the autonomous community (the highest-level administrative unit in Spain) of province d to construct the instrumental variable that I use in my baseline estimation:

$$IV_{o,d}^D = I_{o,-a(d)}^D \times \frac{I_{-c(o),d}^D}{I_{-c(o)}^D} \quad (3)$$

where $a(d)$ is the set of provinces in the autonomous community of d , and $c(o)$ is the set of countries on o 's continent. Therefore, $I_{o,-a(d)}^D$ is the number of immigrants from o settling in Spain outside the autonomous community of province d in decade D , and $I_{-c(o),d}^D/I_{-c(o)}^D$ is the fraction of immigrants to Spain from outside of the continent of o who choose to settle in province d .

One advantage of the leave-out structure of the instrumental variables is that it neatly deals with concerns over reverse causality. For example, drug trafficking organizations may send workers from an origin country to the Spanish provinces to which they hope to traffic drugs. However, these bilateral flows, as well as any historical bilateral flows, are not used for the prediction of the bilateral immigrant population.

The identification assumption is that any confounding factors that make a given province more attractive for both immigration and drug trafficking from a given country do not simultaneously affect the interaction of (i) the settlement of immigrants from other continents with (ii) the total number of immigrants arriving from the same country but settling in a different autonomous community. A violation may occur if, say, immigrants skilled at drug trafficking from Morocco tend to settle in the province of Alicante and immigrants skilled in drug trafficking from Lebanon settle in Barcelona (Barcelona and Alicante are in different autonomous communities) in the same decade and for the same reason: a preference for the familiar Mediterranean climate. Moreover, if Moroccans are a large fraction of immigrants settling in Alicante and Lebanese immigrants are a large fraction of the immigrants settling in Barcelona, then the instrument is predicting bilateral immigration based on a confounding factor: climatic similarity between the immigrants' origin country and the Spanish province.

Finally, to account for spillovers in immigration flows between decades and potential nonlinearities, I also include second-order interaction and squared terms for the instruments,

which allow me to match better the nonlinear immigrant population measure that I use. Nevertheless, my baseline results are robust to more parsimonious sets of instruments.

To measure immigrant inflows, I use the 2001 and 2011 Spanish Census from the National Institute of Statistics distributed by the [Minnesota Population Center \(2019\)](#). From these data, I use respondents' country of nationality, current province of residence in Spain, and year of migration. Since the set of origin countries for which I observe immigrant nationality differs for the two Census waves, I aggregate countries into the smallest consistent units allowable.

3.4 First-Stage

In Figure 4, I plot the residualized first-stage fit of the instruments for the two decades of predicted inflows. All variables are residualized on the set of country and province fixed effects as well as distance. The instruments vary positively with the log number of immigrants, as expected. In Table 2 I show first-stage regressions with different sets of instruments. Instruments from both decades have a positive and statistically significant coefficient across specifications.

In order to better interpret the marginal effect of prediction immigration inflows on the immigrant population, I residualize predicted immigration in 2001–2011 on predicted immigration for 1991–2001. For readability, I divide the instruments by 1,000. The preferred set of instruments that I use in subsequent estimation is the set of instruments and second-order interactions, shown in column 4.

3.5 Results

I now turn to my baseline results on the effect of immigrants on illegal drug confiscations of imports and exports.

Table 3 shows the two-stage least squares estimation results for equation 1 for confiscations of imported drugs. Column 1 shows the result for imports, while column 2 shows the estimate for exports. The coefficient estimate of the effect of immigrants on the likelihood of a confiscation of imported illegal drugs for a country-province pair is 0.163 (SE = 0.046). This estimate implies that at the mean immigrant population at the province-country-pair level, 942, a 10% increase in the number of immigrants raises the likelihood that drugs trafficked from the origin country will be confiscated locally by 0.8 percentage points.²² In

²²Using $\hat{\beta} = 0.163$ from column 1 in Table 3, can compute: $\mathbb{I} \left[C_{o,d,Imports}^{2011-2016} > 0 | M_{o,d}^{2011} = 942 \right] = 0.163 \left(\ln \left(1 + \frac{942 \times 1.1}{1000} \right) - \ln \left(1 + \frac{942}{1000} \right) \right) \approx 0.0077$.

comparison, 8.4% of country-province pairs confiscated some amount of illegal drugs being imported into Spain.

In column 2, I find that immigrants also increase exports of illegal drugs. The coefficient estimate is 0.0579 (SE=0.0348). This estimate implies that a 10% increase in the number of immigrants relative to the mean raises the likelihood that drugs will be exports to the immigrants' origin country and confiscated locally by 0.3 percentage points.²³

There are two biases relative to the OLS to take account of. First, there may be confounding variables at the country-province-pair level which drive both immigration and drug trafficking between locations. These confounders will tend to bias the OLS estimates upwards. Second, the number of immigrants from a given country living in a Spanish province may be mismeasured, biasing the OLS estimates downwards. My two-stage least squares estimates are statistically indistinguishable from the OLS estimates, which suggests that after controlling for a rich set of fixed effects, bilateral confounders do not substantially impact on the OLS estimates.

3.6 Preferences for Drugs and Trade Costs

After controlling for the institutions and labor market conditions of the host province and origin country, more immigrants may raise imports of illicit drugs for two reasons. First, they may prefer to consume goods imported from their home country. Second, immigrants reduce trade costs between origin and destination.

Immigrant Preferences. [Atkin \(2013\)](#) and [Bronnenberg et al. \(2012\)](#) suggest that immigrants may share the same tastes for food and other products as consumers in their origin country. If these similar tastes also apply to illicit drugs, more drugs may be trafficked from immigrants' origin country. However, such a story would require retail drug consumers to have an implausible combination of tastes and information. Consider an immigrant from Venezuela who consumes cocaine. This immigrant would need to be able to distinguish street cocaine based on which country it was trafficked from (not produced in). However, since the modifications to cocaine generally occur close to the point of production and in any case do not differ much based on production location, it is unlikely that the immigrant's experience would differ much based on which country the cocaine was trafficked through.

I also compare drug use between immigrants and native-born Spaniards and find that immigrants consume drugs at a substantially lower rate. Using the EDADES data introduced

²³Using $\hat{\beta} = 0.0579$ from column 2 in Table 3, can compute: $\mathbb{I} \left[C_{d,o}^{2011-2016} > 0 | M_{o,d}^{2011} = 942 \right] = 0.0579 \left(\ln \left(1 + \frac{942 \times 1.1}{1000} \right) - \ln \left(1 + \frac{942}{1000} \right) \right) \approx 0.0027$.

in Section 2.3 for the years 2005 through 2015, I find that 22% of those born outside of Spain have ever consumed cannabis, cocaine, heroin, or amphetamines compared to nearly 35% of native-born Spaniards. Taken together, these facts suggest immigrants bringing the demand for drugs from their home country with them to Spain are unlikely to explain my baseline results.

Trade Costs. Immigrants may increase illegal trade in much the same way they raise legal trade. Felbermayr et al. (2015) note that immigrant networks can reduce information and search frictions for trade between two locations, since trust may be greater within nationality and information travels more smoothly within nationality group. Additionally, immigrant networks raise the cost of opportunistic or cheating behavior by firms within the nationality network, who can be punished for bad behavior by being shunned from business within the network (Rauch and Trindade, 2002). Finally, the qualitative studies summarized in Section 2.1 demonstrate ways in which social connections between immigrants can facilitate trafficking by reducing trade costs.

In the context of this study, I find that immigrants raise drug flows on both the import and export margins. The fact that immigrants increase exports suggest that immigrants reduce trade costs rather than simply raise demand for drugs.

3.7 Value of Drugs Confiscated

I also estimate the effect of immigrants on the value of drugs confiscated. In order to measure the value of the dependent variable in logs and include zero values, I use pseudo-Poisson maximum likelihood estimation (PPML) (Silva and Tenreyro, 2006). Due to the non-linearity of PPML, I take a control function approach to generating exogenous variation in the immigrant population (Petrin and Train, 2010; Morten and Oliveira, 2016).

In particular, I estimate the first-stage as in column 4 of Table 2 and add the residuals to the PPML estimating equation. The PPML first-order condition is then

$$\sum_{o,d} (Value\ confiscated_{o,d}^{2011-2016} - \exp(\delta_o + \delta_d + \beta M_{o,d}^{2011} + \zeta \hat{\epsilon}_{o,d}^M + \gamma \ln(Dist_{o,d})) X_{o,d} = 0 \quad (4)$$

where $Value\ confiscated_{o,d}^{2011-2016}$ is the value in dollars of illegal drugs confiscated between country o and province d ; $\hat{\epsilon}_{o,d}^M$ is the first-stage residual; and $X_{o,d}$ is the vector of variables included in the exponential function (i.e., dummies for countries and provinces, $M_{o,d}^{2011}$, $\hat{\epsilon}_{o,d}^M$, and $\ln(Dist_{o,d})$). I estimate equation 4 separately for imports and exports as in the baseline

estimation.

I show the results of the PPML estimation in Table 4.²⁴ In columns 1 and 3, I estimate the effect of immigrants on import and export confiscation values, respectively, without including the first-stage residuals. In columns 2 and 4 I add the first-stage residuals.

Consistent with my baseline results, I find that immigrants increase the value of drugs imported and exported. In particular, the coefficient estimate of the effect of immigrants on the value of imported illegal drugs for a country-province pair is 0.481 (SE = 0.249). This estimate implies that a 10% increase in the number of immigrants relative to the mean raises the value of drugs trafficked from the origin country will be confiscated locally by 2.3%.²⁵

Turning to the effect of immigrants on the value of drug exports, the estimated coefficient is 0.644 (SE=0.35). This estimate implies that a 10% increase in the number of immigrants relative to the mean raises the value of drugs trafficked from the origin country will be confiscated locally by 3%.²⁶

3.8 Drug-Hub Level of Immigrant’s Origin Country

To understand the degree to which the immigrant-trafficking relationship is heterogenous by origin country, I look at whether drugs being confiscated are coming from countries that are hubs of drug trafficking.²⁷ I re-estimate equation 1, interacting the country-province immigrant log population with the drug-hub level of the immigrants’ origin country.²⁸ I measure country o drug-hubness in two ways. First, as the fraction of world drug confiscations that originate in country o , and second, as the ordinal rank of country o in the fraction of world drug confiscations originated.

In Table 9, I show the estimated coefficients. As I show in columns 1 and 3, origin countries that send a substantial amount of illicit drugs to countries other than Spain are

²⁴Note that my sample size drops in the PPML relative to my baseline. This is because PPML estimates for countries or provinces that never experience drug confiscations will not exist given my inclusion of country and province fixed effects (Silva and Tenreyro, 2010). Correia et al. (2019) argue that it is best to drop such “separated” observations from the estimation since they do not contribute to the estimation of β . For all PPML estimates, I use the methods developed by Correia et al. (2020).

²⁵Using $\hat{\beta} = 0.481$ from column 2 in Table 4 and a mean bilateral immigrant population of 942, we have:

$$\frac{C_{o,d}^{2011-2016}[M_{o,d}^{2011}=1.1 \times 942]}{C_{o,d}^{2011-2016}[M_{o,d}^{2011}=942]} - 1 = \exp\left(0.481\left(\ln\left(1 + \frac{1.1 \times 942}{1000}\right) - \ln\left(1 + \frac{942}{1000}\right)\right)\right) - 1 = 0.023.$$

²⁶Using $\hat{\beta} = 0.644$ from column 4 in Table 4 and a mean bilateral immigrant population of 942, we have:

$$\frac{C_{d,o}^{2011-2016}[M_{o,d}^{2011}=1.1 \times 942]}{C_{d,o}^{2011-2016}[M_{o,d}^{2011}=942]} - 1 = \exp\left(0.644\left(\ln\left(1 + \frac{1.1 \times 942}{1000}\right) - \ln\left(1 + \frac{942}{1000}\right)\right)\right) - 1 = 0.03.$$

²⁷I define the drug-hub level of a given country as either the fraction of global drug confiscations for which the country was the exporter or the rank order thereof.

²⁸Data on world bilateral drug confiscations are taken from the same UNODC dataset on individual drug confiscations that I use for Spain. One drawback of these data for countries other than Spain is that reporting drug confiscations to the UNODC occurs less frequently and is of lower quality. Nevertheless, no alternative data source on country-pair drug trafficking exists, so I pursue this analysis using these imperfect data.

more likely to export drugs to Spain when more immigrants from those countries settle in Spain. I also find some evidence that immigrants from drug hub countries facilitate the export of illegal drugs to their home country, as shown in columns 2 and 4.

3.9 Robustness Checks

In my baseline analysis, I make specific assumptions on my functional form, sample, and specification. Below, I show that my baseline results are robust to variations on each of these dimensions.

3.9.1 Relaxing Functional Form Assumption

In my baseline specification, equation 1, I measure the endogenous variable of interest as the log of one plus the number of immigrants measured in thousands: $\ln\left(1 + \frac{\# \text{migrants}_{o,d}^{2011}}{1000}\right)$.²⁹ To test whether my results are sensitive to changes in the function form of the endogenous variable, I perform two robustness exercises.

First, I estimate my baseline specification across various alternative functional forms for the number of immigrants. I show the results in Table 10. Across functional forms, more immigrants lead to more drug confiscations, as I find in the baseline.

Next, I relax the functional form assumption of my baseline specification that $\pi = \frac{1}{1000}$ for the independent variable $\ln\left(1 + \pi \times \# \text{migrants}_{o,d}^{2011}\right)$. To do so, I estimate π in my baseline specification using nonlinear Generalized Method of Moments. Specifically, I simultaneously estimate the two baseline gravity equations for imports and exports,

$$\begin{aligned} \mathbf{1}[C_{o,d}^{2011-2016} > 0] &= \alpha_o^{Import} + \alpha_d^{Import} + \beta^{Import} \ln(1 + \pi \times \# \text{migrants}_{o,d}^{2011}) + \delta^{Import} \ln(Dist_{o,d}) + \epsilon_{o,d}^{Import} \\ \mathbf{1}[C_{d,o}^{2011-2016} > 0] &= \alpha_o^{Export} + \alpha_d^{Export} + \beta^{Export} \ln(1 + \pi \times \# \text{migrants}_{o,d}^{2011}) + \delta^{Export} \ln(Dist_{o,d}) + \epsilon_{o,d}^{Export} \end{aligned} \quad (5)$$

with moment conditions

$$E[\mathbf{Z}_{o,d} \times (Y_{o,d} - \alpha_o - \alpha_d - \beta \ln(\pi \times \# \text{migrants}_{o,d}^{2011} + 1) - \delta \ln(Dist_{o,d}))] = \mathbf{0}$$

²⁹I motivate my choice of a log-functional form with the binscatter plot in Figure 21 of the relationship between the immigrant population and the dummy variable for whether any confiscation occurs at the country-province level.

$$E \left[\begin{pmatrix} \alpha_o \\ \alpha_d \end{pmatrix} \times (Y_{o,d} - \alpha_o - \alpha_d - \beta \ln(\pi \times \# \text{migrants}_{o,d}^{2011} + 1) - \delta \ln(\text{Dist}_{o,d})) \right] = \mathbf{0}$$

for dependent variable $Y_{o,d} = (\mathbf{1}[C_{o,d}^{2011-2016} > 0], \mathbf{1}[C_{d,o}^{2011-2016} > 0])'$, fixed effects $\alpha_i = (\alpha_i^{Import}, \alpha_i^{Export})$, parameters $\beta = (\beta^{Import}, \beta^{Export})$ and $\delta = (\delta^{Import}, \delta^{Export})$, and instrument set $\mathbf{Z}_{o,d}$ as in my baseline estimation (i.e., column 4 of Table 2).

Table 11 shows the results. My estimate of π does not reject my baseline functional form assumption of $\pi = \frac{1}{1000}$ and rejects the more conventional functional form choice $\pi = 1$.³⁰ In addition, the estimates of (β_1, β_2) also are statistically indistinguishable from my baseline coefficient estimates.

3.9.2 Varying Estimation Sample

Drug trafficking into Spain is primarily driven by a select few countries—Morocco, for example, is the dominant exporter of cannabis to Spain. To see whether any particular origin country drives my baseline results, I re-estimate the gravity specification, leaving out individual countries. Figure 19 shows the distribution of β estimates from equation 1 when I drop one origin country at a time for both dependent variables, $\mathbf{1}[C_{o,d}^{2011-2016} > 0]$ and $\mathbf{1}[C_{d,o}^{2011-2016} > 0]$. The histograms show that I estimate a positive β regardless of which country I drop from the sample, suggesting that no single country drives the results.

I also explore the heterogeneity of the effect of immigrants on drug trafficking across individual countries and Spanish provinces. In Figure 18, I plot coefficients on the immigrant population's effect on imports (top row) and exports (bottom row) across provinces (left column) and countries (right column). The red curve displays the threshold for statistical significance at the 10% level, with circle size corresponding to province population or nationality population. I find that nearly all individual provinces and countries exhibit a positive effect of immigrants on illegal trafficking, with most coefficients being statistically significant.

Finally, I estimate the immigrant-confiscations relationship separately by the two major drugs trafficked in Spain: cannabis and cocaine. I estimate positive and statistically significant effect sizes for both imports and exports across both drugs. Cocaine imports are more significantly raised by immigrants than cannabis, consistent with the fact that cocaine must be imported, whereas cannabis can be produced locally in Spain.

³⁰Note that my standard errors are not adjusted for being constrained to ensure that $X > 0$ in $\ln(X)$ as suggested by Andrews (2002).

3.9.3 Standard Errors

In my baseline specification, I cluster standard errors at the country level. To test whether my results are robust to alternative standard error clustering, including two-way clustering, I re-estimate my baseline specification using various different clustering geographies. Table 12 shows these estimates, which remain statistically significant across the different clustering geographies for imports and exports. Moreover, the clustering geography used in my baseline estimation, country-level, produces the largest standard errors.

3.9.4 Panel Estimation

I interpret my baseline cross-sectional estimates as representing the long-run effect of immigrants on drug trafficking. However, I can also estimate a panel specification to take advantage of year-to-year variation in immigration and drug trafficking.

I estimate the panel with the same specification as in my baseline, but adding time-superscripts:

$$Y_{o,d}^t = \alpha_o^t + \alpha_d^t + \beta M_{o,d}^t + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d}^t \quad (6)$$

where $Y_{o,d}^t \in \{1 [C_{o,d}^t > 0], 1 [C_{d,o}^t > 0]\}$, a dummy for whether any imports or export of illegal drugs were confiscated by Spanish authorities, respectively. $M_{o,d}^t$ is defined as before and measured using annual tabulations taken from Spain's local population registries at the country-province-year level.

I also estimate the panel including country-province fixed effects:

$$Y_{o,d}^t = \alpha_o^t + \alpha_d^t + \beta M_{o,d}^t + \alpha_{o,d} + \varepsilon_{o,d}^t \quad (7)$$

These fixed effects absorb time-invariant bilateral characteristics, such as climatic or geographic similarity. However, the o, d fixed effects change the interpretation of β . In particular, β represents the change in illegal drug trafficking resulting from year-to-year net changes in the immigrant population. Therefore, equation 7 sheds light on the effect of recent immigrants on illegal trafficking, but it does not test whether long-run migrant networks shape illegal trafficking.

To achieve causal identification, I use the instrumental defined in equation 3 for the decade 1991–2001:

$$IV_{o,d}^{1991-2001} = I_{o,-a(d)}^{1991-2001} \times \frac{I_{-c(o),d}^{1991-2001}}{I_{-c(o)}^{1991-2001}} \quad (8)$$

In addition, I include a time-varying instrument that predicts bilateral immigrant inflows between 2001 and year t ,

$$IV_{o,d}^t = I_{o,-a(d)}^{2001-t} \times \frac{I_{-c(o),d}^{2001-t}}{I_{-c(o)}^{2001-t}} \quad (9)$$

I compute immigrant inflows between 2001 and t as the net change in the bilateral immigrant population as measured in the population registry. Consistent with my baseline specification, I include interaction and squared terms when estimating the first-stage. I estimate equations 6 and 7 for the years 2003 through 2016.

I find that immigrants raise imports and exports, consistent with my baseline results. For imports, a 10% increase in the population of immigrants from country o raises the likelihood of imports by 0.9 percentage points³¹ without o, d fixed effects or by 1.4 percentage points when including o, d fixed effects. For exports, a 10% increase in immigrants from o raises the likelihood of illegal drug exports to o by 0.2 percentage points (without o, d fixed effect) or by 0.6 percentage points (with o, d fixed effects).

A drawback of the panel is that both immigrant population and drug trafficking may be less well measured from year to year. For immigrant population, which I measure using local population registries, entries may be updated with some lag, and therefore mismeasure the local immigrant population. Drug confiscations may vary wildly from year to year, as police come across a huge, multi-million dollar seizure in one year but not the next. Such variation may not reflect actual changes in drug smuggling routes. Therefore, I retain the cross-section as my baseline with immigrant populations measured using the decennial census and drug confiscations pooled across several years.

3.9.5 Legal Trade

To see whether immigrants have a similar effect on legal trade as on illegal trade, I estimate the relationship between the bilateral immigrant population and legal imports and exports. To measure legal trade volume, I use the ADUANAS-AEAT dataset provided by the Spanish government. This dataset provides transaction-level data and includes information on the origin (for imports) or destination (for exports) country and the same for the origin or destination province within Spain. I aggregate these data to the province-by-origin country level for imports for the years 2011 to 2016.

As in Section 3.7, I take a control function pseudo-Poisson maximum likelihood estimation approach. I show the results in Table 14. Consistent with Burchardi et al. (2019), I find no

³¹Using $\hat{\beta} = 0.185$ from column 1 in Table 13, can compute: $\mathbb{I} \left[C_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 942 \right] = 0.185 \left(\ln \left(1 + \frac{942 \times 1.1}{1000} \right) - \ln \left(1 + \frac{942}{1000} \right) \right) \approx 0.0088$.

statistically significant effect of immigrants on legal imports (column 1) or exports (column 2). One potential explanation for the discrepancy between the effect of immigrants on legal versus illegal trade is that with illegal trade, immigrants have to rely even more on informal social ties than with legal trade. Legal institutions exist to facilitate the flow of legal trade, thus offsetting some of the need for informal ties.

4 Enforcement Intensity and General Equilibrium Responses

My gravity estimates may not imply that overall illegal drug market activity rises with additional migration for two reasons. First, increases in the bilateral immigrant population may increase the scrutiny of law enforcement, thus resulting in the relationship estimated in Section 3.5 but not corresponding to a real rise in actual drug flows. Second, increases in trafficking may be offset by decreases in local production or decreases in imports on other bilateral links. I do not find evidence for either of these channels, as I show below.

4.1 Enforcement Intensity

In Section 2.3 I showed that drug confiscations correspond to drug use and availability at the *province level*. In my bilateral estimation, I control for enforcement intensity specific to each Spanish province (and common across all origins) as well as for enforcement intensity specific to each origin country (but common to all Spanish provinces). In this section, I conduct an exercise at the *bilateral level* to assess the extent to which variation in bilateral enforcement intensity drives my baseline results from Section 3. I also conduct an additional test for the extent to which enforcement intensity drives confiscations in Appendix B.1 leveraging plausible changes in enforcement intensity following the 2004 Madrid bombing.

I use the intuition that for bilateral links near the extensive margin of trafficking drugs, enforcement changes caused by variation in the number of immigrants will not be important in driving confiscations. To formalize the intuition, note that confiscations are a product of enforcement intensity and actual drug flows: $C_{o,d} = E_{o,d}D_{o,d}$, where $C_{o,d}$ is the value of drugs confiscated between o and d , $E_{o,d}$ is the fraction of drugs confiscated, and $D_{o,d}$ is the actual flow of drugs from o to d . Taking the derivative with respect to the number of immigrants, I get

$$\frac{dC_{o,d}}{dM_{o,d}} = E_{o,d} \frac{\partial D_{o,d}}{\partial M_{o,d}} + D_{o,d} \frac{\partial E_{o,d}}{\partial M_{o,d}} \quad (10)$$

Dividing equation 10 by the value of drugs confiscated $C_{o,d}$ and multiplying by the immigrant population $M_{o,d}$, I obtain

$$\epsilon_{C,M} = \epsilon_{D,M} + \epsilon_{E,M} \quad (11)$$

where $\epsilon_{a,b}$ is the elasticity of a with respect to b .

In my baseline estimation, I assume that $\frac{\partial E_{o,d}}{\partial M_{o,d}} = 0$ in equation 10, allowing me to estimate the object of interest, $\frac{\partial D_{o,d}}{\partial M_{o,d}}$. However, my estimation will also pick up changes in bilateral enforcement intensity that result from changes in bilateral migration, $\frac{\partial E_{o,d}}{\partial M_{o,d}}$. This may occur if, for example, police target immigrant groups for drug trafficking enforcement actions once that group reaches a critical mass.

To test this assumption and gauge the extent to which enforcement intensity variation may affect my results, I estimate

$$Y_{o,d} = \alpha_o + \alpha_d + \beta M_{o,d} + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d} \quad (12)$$

for the subset of observations for which I predict that $X_{o,d} \approx 0$, with $Y_{o,d}$ either a dummy for any import confiscation or any export confiscation.³²

To predict when actual flows $D_{od} \approx 0$, I use a similar leave-out push-pull structure for confiscations between 2011 and 2016 as I did for immigrant inflows:

$$\hat{C}_{o,d} = C_{o,-a(d)} \times \frac{C_{-c(o),d}}{C_{-c(o)}} \quad (13)$$

where $\hat{C}_{o,d}$ interacts confiscations of drugs originating from o but confiscated outside the autonomous community of d with the fraction of all drugs from outside o 's continent confiscated in d . Implicit in this formulation is the assumption that (1) on average, law enforcement in province d will discriminate differently against immigrants from continents outside of $c(o)$, and (2) on average, law enforcement in other autonomous communities will discriminate differently against immigrants from o .

I show results in Table 5 subsetting to bilateral links that I predict having less than \$15,000 worth of drugs confiscated. While the point estimate falls when subsetting to the sample predicted to be on the extensive margin, the extensive margin estimate in column 2 remains statistically significantly positive, suggesting enforcement variation cannot fully explain my bilateral results. For the results on exports shown in columns 3 and 4, I find a modest decline in the coefficient, with a loss of statistical significance in column 4.

³²Akee et al. (2014) similarly focus on the extensive margin when estimating the determinants of transnational human trafficking.

4.2 General Equilibrium Responses

While I have shown that more immigrants on a bilateral link raise bilateral drug confiscations, this effect may be offset by general equilibrium adjustments to immigrant-induced trafficking. For example, trafficker immigrants from one country may reduce their trafficking in response to more immigration from another country. If such adjustments offset the effect of immigrants on trafficking, then there should be no effect when aggregating across origin countries. To assess the strength of the general equilibrium response, I estimate the effect of immigrants on drug market activity at the province level.

4.2.1 Drug Confiscations, Use, and Arrests

I first estimate the effect of immigrants on confiscations of illegal drugs, illegal drug use, and drug trafficking arrests with a panel of Spanish provinces. For the years 2003 to 2016, I estimate

$$\ln Y_d^t = \alpha_d + \alpha^t + \beta \ln M_d^t + \epsilon_d^t \quad (14)$$

for some measure Y_d of illegal drug activity in d and the log number of immigrants from all origins M_d^t in year t . I also control for province and year fixed effects and cluster standard errors at the autonomous community-by-year level. Because there might be factors affecting both immigration and drug smuggling into a province, I instrument for the immigrant population using the shift-share instrumental variable from [Cortes \(2008\)](#):

$$IV_d^t = \ln \left[\sum_o \left(\frac{Immigrants_{o,d}^{1981}}{Immigrants_o^{1981}} \right) \times Immigrants_o^t \right] \quad (15)$$

where $Immigrants_o^t$ refers to the number of immigrants from o living in Spain in year t .³³

Because I am exploiting less variation than in my baseline gravity estimation, interpreting β as the causal effect of immigrant share on drug activity requires a stronger identifying assumption, as I can no longer exploit variation across immigrant origins. In particular, my identification assumption requires that there are no persistent shocks within province that shape the distribution of immigrant populations in 1981, the distribution of immigrant populations in the 2000s, and the distribution of drug trafficking across space in the 2000s.

In [Figure 22](#) I show the first-stage fit. The instrument positively predicts the immigrant population across Spanish provinces over time.

³³I also use a jackknife version of equation 15 in which I leave out province d , that is $IV_d^t = \ln \left[\sum_o \left(\frac{Immigrants_{o,d}^{1981}}{Immigrants_o^{1981}} \right) \times Immigrants_{o,-d}^t \right]$. I show results in [Table 15](#).

I estimate equation 14 with dependent variable C_d^t , the log value of drugs confiscated in province d in year t . Column 2 of Table 6 shows the result. I find that a 1% increase in immigrant population share in a province raises drug smuggling into that province by almost 22% (SE=11.6) overall. This elasticity of immigrant population to illegal drugs imported is higher than my baseline estimates, suggesting general equilibrium adjustment (such as trade diversion) to trafficking by immigrants does not offset the effect of immigrants on trafficking.

I next estimate equation 14 with dependent variable the log of the number of native-born drug users measured using the biennial EDADES survey described in Section 2.3. I find no effect of immigrants on the drug use of the native-born as shown in columns 3 and 4 of Table 6, perhaps because immigrant-induced drug trafficking is mostly re-exported, and is therefore not intended for use in the local market. However, despite the weak first-stage, both estimates are positive.

Finally, I explore the effect of immigrants on the arrests of native-born Spaniards for drug trafficking in column 5. I find that increased immigration drives down arrests of native-born Spaniards for drug trafficking, suggesting potential substitution of the native-born for immigrants in trafficking. However, the coefficient is quite imprecisely estimated.

4.2.2 Cannabis Cultivation

Next, I estimate the effect of the immigrant population on the domestic cultivation of cannabis. Due to a lack of data, I use a single cross-section of Spanish provinces. I estimate

$$\ln Cannabis\ plants\ seized_d = \alpha + \beta \ln M_d^{2011} + \gamma \ln Population_d^{1981} + \epsilon_d \quad (16)$$

for $\ln Cannabis\ plants\ seized_d$ the number of cannabis plants confiscated from growhouses in Spanish province d and the log number of immigrants from all origins $\ln M_d^{2011}$ in 2011. I again use the shift-share instrumental variable defined in equation 15.

Spain produces a small but non-trivial amount of cannabis.³⁴ I draw on Alvarez et al. (2016), who assemble a dataset on cannabis plant confiscations based on 2013 press reports and public statements by the Spanish government.³⁵ As I show in Table 7, I find that as the

³⁴Alvarez et al. (2016) find that in 2013, authorities confiscated almost 200,000 cannabis plants growing in Spain. Combining the United Nations' estimate of the average weight of a cannabis plant (p. 39, UNODC, 2017) with the estimate of wholesale prices of cannabis herb in Spain for 2013, the confiscated plants are valued at approximately \$26 million. This compares to about \$312 million in confiscated cannabis coming from outside Spain.

³⁵I do not have access to the microdata compiled by Alvarez et al. (2016), but instead use the approximate number of plants confiscated by province derived from their Figure 4. This leads to some measurement error. Moreover, I do not observe confiscations in the provinces of Ceuta or Mellila.

local immigrant population increases, there is an increase in the number of cannabis plants confiscated locally, suggesting that local production of illegal drugs rises with increased immigrant drug trafficking.

5 Legal Status, Naturalization, and Trafficking

Immigrants' integration into labor markets and civil society may be hampered when they do not have legal status. A lack of legal status may hinder their access to the formal labor market, lowering the opportunity cost of crime (Becker, 1968; Ehrlich, 1973). This lower opportunity cost may increase in criminal activity among immigrants, as found empirically by Mastrobuoni and Pinotti (2015), Pinotti (2017), and Freedman et al. (2018), especially in financially motivated crime such as drug trafficking.

To assess whether this intuition holds for drug trafficking, I conduct two exercises. First, I estimate a gravity equation to test the effect of irregular immigrants (those without legal status) and regular immigrants on drug confiscations and find that irregular immigrants for imports drive my baseline gravity results, but regular immigrants for exports. Second, I exploit an extraordinary immigrant legalization program in 2005 and find that granting immigrants legal status can significantly reduce illegal drug imports.

5.1 Measuring the Irregular Immigrant Population

To estimate the prevalence of irregular immigrants at the origin country-destination province level, I take the difference between the number of persons appearing in the population registry of province d from origin country o and the number of persons with residency permits in province d from country o . Specifically, I compute

$$Irregular\ Migrants_{od} = Population\ Registry\ Count_{od} - Residency\ Permits_{od} \quad (17)$$

and then divide by the total bilateral immigrant population to obtain the fraction of immigrants who have irregular status.

I do this for all 52 Spanish provinces as well as for the 75 origin countries for which I observe bilateral population registry figures and bilateral residency permits in 2011. I estimate that 27% of immigrants living in Spain are irregular, consistent with the estimate from González-Enríquez (2009) in 2008.

5.2 Gravity Estimation by Legal Status

To explore whether immigrant legal status can explain the connection I find between immigrants and drug trafficking, I modify my baseline specification to include two separate terms for the bilateral immigrant population in 2011 by regular ($M_{o,d}^{reg}$) and irregular ($M_{o,d}^{irreg}$) status:

$$Y_{o,d} = \alpha_o + \alpha_d + \beta_{irreg} M_{o,d}^{irreg} + \beta_{reg} M_{o,d}^{reg} + \zeta \ln(Dist_{o,d}) + \varepsilon_{o,d} \quad (18)$$

where, as in equation 1, $Y_{o,d}$ is a dummy for any drugs trafficked between o and d were confiscated by Spanish authorities, estimated separately for import and export confiscations. Thus β_{irreg} is the effect of irregular immigrants on trafficking and β_{reg} is the effect of regular immigrants on trafficking.

Separating immigrants by legal status introduces another endogeneity issue—differential selection of immigrants into legal status and trafficking—which the baseline leave-out push-pull instrument defined in equation 3 may not address. For example, some immigrants with a higher taste for risk may be more likely to be irregular and participate in illegal drug trafficking. To the extent that this selection is common across provinces for a given nationality, the country fixed effect α_o will absorb such selection. Similarly, if the characteristic is common across immigrants of different nationalities in a given province, the province fixed effect α_d will absorb this common preference for risk-taking.

To address province-country-specific selection into irregularity and drug trafficking, I modify the leave-out push-pull instrument predicting immigrant inflows to predict immigrant inflows by legal status. In particular, I interact the leave-out push-pull instrument ($IV_{o,d}^D$ from equation 3) with the lagged leave-out fraction of immigrants with legal status L ,

$$IV_{o,d}^{D,L} = m_{o,d}^L \times IV_{o,d}^D \quad (19)$$

for $L \in \{regular, irregular\}$ and decade D , where $m_{o,d}^L = \frac{immigrants_{o,-a(d)}^{2003,L}}{immigrants_{o,-a(d)}^{2003}}$, the fraction of immigrants with legal status L from country o who live outside the autonomous community of province d back in 2003, the earliest year with data on immigrant legal status at the country-province level. The instrument interacts variation across three dimensions: (i) immigration from various origin countries, (ii) immigration to various Spanish provinces, and (iii) the propensity of immigrants to have legal status L at the country-province level.

The identification restriction is that there are no confounders persistent from 2003 to 2011 and present in both province d and another province outside d 's autonomous community—at the country-province level driving selection of immigrants into both irregular status and drug

trafficking. For example, suppose we want to predict the fraction of irregular Moroccan immigrants living in Barcelona in 2011. $m_{o,d}^L$ uses information on the legal status of Moroccan immigrants outside Catalonia (the autonomous community of Barcelona) back in 2003 to predict the 2011 legal status of Moroccans in Barcelona. The exclusion restriction is violated if, say, Moroccans in Madrid in 2003 were driven into irregularity and drug trafficking by the same confounder (e.g., a preference for risk-taking) that drove Moroccans in Barcelona in 2011 into irregularity and trafficking. This endogeneity will meaningfully affect the estimation so long as a non-trivial share of Moroccans outside Catalonia live in Madrid and the confounder acts disproportionately on Moroccans in Madrid than on Moroccans elsewhere (i.e., it is not absorbed by the Moroccan fixed effect).

I show the results in Table 8. I find that a 10% increase in the bilateral *irregular* immigrant population raises the likelihood of an illegal drug import confiscation by 0.7 percentage points. By contrast, a 10% increase in the *regular* immigrant population raises the likelihood of illegal drug imports by 0.4 percentage points, though the estimated coefficient is statistically insignificant.³⁶ I also find that regular immigrants increase illegal drug exports, while irregular immigrants reduce them, as shown in column 2 of Table 8.

While this finding may be inconsistent at first glance with the Becker model of crime, it is consistent with the logistical context of drug trafficking in Europe. First, I note that the most important export destinations of drugs leaving Spain are European Union member states (see Figure 13). Immigrants from E.U. countries cannot be irregular in Spain. Second, much of the within-Europe trafficking is conducted by small wholesale distribution companies with a fleet of trucks. Taking advantage of the E.U.’s borderless environment facilitates the flow of illegal goods as much as it does legal goods.³⁷ Such companies are much more likely to be owned and operated by persons other than irregular immigrants.

These results suggest immigrant legal status is an important factor shaping immigrants’ role in drug trafficking. However, the composition of immigrants for a given country-province pair may differ based on the immigrants’ legal status. For example, if Moroccan immigrants in Barcelona in 2011 are disproportionately risk-loving, which induces some of them into trafficking drugs and into irregularity, and this pattern occurred in 2003 Madrid as well, then the instrument and fixed effects will not adequately control for such selection. To better

³⁶Using $\hat{\beta}^{Irreg} = 0.152$ from column 1 and mean value of bilateral immigrant population of 942, I find that $\mathbb{1} \left[C_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 942 \right] = 0.152 \left(\ln \left(1 + \frac{942 \times 1.1}{1000} \right) - \ln \left(1 + \frac{942}{1000} \right) \right) \approx 0.0072$ and for $\hat{\beta}^{Reg} = 0.0911$, this is 0.004, albeit statistically indistinguishable from 0.

³⁷Fukumi (2008) notes that “the introduction of the Schengen Agreement in 1985, and the full implementation of the Schengen Treaty in 1995 opened a window of opportunity to cocaine traffickers because it enabled free movement within a major part of Western Europe.” (p. 50) She further argues that drug traffickers often launder money by buying import and export companies, commodity trading businesses, and cargo businesses, which are all useful in transporting illegal drugs (p. 54).

understand the role immigration policy can play in mitigating the immigrant-trafficking relationship, I turn to an event study of a major immigrant regularization.

5.3 2005 Mass Regularization Event Study

In 2005, Spain conducted the largest regularization event of immigrants in its history, with over half a million immigrants obtaining legal status. Immigrants who were registered with their local council in the population registry as of August 8, 2004, were offered a work contract of at least six months (three months if in agriculture), and had no criminal record in their home country or in Spain, were eligible to apply for regular status, usually through their prospective employer (González-Enríquez, 2009). I find that the 2005 regularization led to a sharp increase in the number of work authorizations granted to immigrants in Spain, as shown in Figure 23.

To better understand the effects of the regularization, I estimate a simple event study at the country-by-quarter level. The event study differs from my baseline cross-section estimates in Section 3.2 in that I use higher frequency quarterly variation in drug confiscations. I do so for two reasons. First, I prefer nationality-level aggregation because the policy differentially affected immigrants depending on their country of origin. For example, immigrants from the E.U. were not impacted by the policy since the Schengen Agreement precludes irregularity. In addition, at the bilateral level, confiscations can occur highly irregularly, with no confiscations for several years followed by a year with one massive confiscation. This volatility is likely more a result of variation in enforcement “luck” rather than changes in actual flows of illicit drugs, and therefore it reflects measurement error. To smooth out this variation and thereby obtain more precise estimates, I aggregate to the country-quarter level.

I estimate the event study using the equation

$$Y_o^t = \sum_{t \neq 2004q4} \theta^t \times \text{Frac. irregular}_o^{2003} + \delta_o + \delta^t + \epsilon_o^t \quad (20)$$

where $\text{Frac. irregular}_o^{2003}$ is the fraction of immigrants in 2003 without legal status, as imputed using equation 17. I estimate the event study for the years 2000 through 2008, choosing the end-year cutoff to avoid conflating any effects with the Great Recession.

I plot the θ^t coefficients in Figure 5 with the dependent variable a dummy for whether any import confiscation occurred. I show the 2005 regularization reduced the likelihood of any import drug confiscation and remained lower thereafter. Moreover, this decline came primarily from declines in cocaine confiscations, as shown in Figure 6, with no change observed in cannabis confiscations. I find a modest increase in export confiscations, as shown

in Figure 24, although pre-intervention coefficients are often significantly higher than zero, suggesting there may be pre-trends in exports.

I hypothesize that the discrepancy in the effect of the legalization program between cannabis and cocaine imports may be due to the differential treatment of Moroccan versus Latin American immigrants in Spain. In particular, Moroccan immigrants face a much more difficult road towards obtaining Spanish citizenship, being required to be in the country legally for ten consecutive years (see Figure 25). In contrast, Latin American immigrants are only required to be present for two consecutive years before becoming eligible for citizenship. In addition, Latin American immigrants are more likely to natively speak Spanish and thus face an easier time culturally and economically assimilating into Spanish society.

Overall, the event study results suggest that granting legal status to immigrants plays an important role in reducing drug trafficking, potentially by putting them on a path to citizenship. Taking the average of the coefficients from 2005 to 2008 for the event study estimated on the extensive margin of illegal imports suggests that granting 10% of immigrants legal status reduces the likelihood of import trafficking of any drug by 1.4 percentage points and of cocaine specifically by 2 percentage points.

6 Conclusion

The effect of immigration on crime has long been a controversial political issue. In this paper, I contribute to this debate by causally estimating that international immigration is an important factor shaping international drug trafficking, on par with the effect immigrants have on legal trade. This effect is driven primarily by immigrants without legal status, and my evidence shows that granting legal status and a path to citizenship to immigrants can significantly diminish this relationship.

The results presented here have significant relevance to ongoing debates on immigration policy in the United States and around the world. In particular, as many European countries and the United States discuss providing some form of amnesty and a path to citizenship to their large populations of undocumented immigrants, this paper offers an additional potential benefit to society from such amnesties. Providing amnesty is also likely to be much cheaper than attempting to keep irregular immigrants from entering the country, such as building a wall. For example, Allen et al. (2018) estimate that the 2007–2010 expansion of the border wall on the U.S.-Mexico border cost approximately \$57,500 per deterred immigrant.

An important caveat is that immigrants generate a range of effects on their host countries, from native-born wages to innovation to consumer choice. Hence, generalizing welfare effects of immigration from just one outcome, as is the subject of the present study, may lead to

suboptimal policy choices. Instead, policymakers must weigh the varied impacts of migration when shaping immigration policy.

This paper suggests several lines of future research. Subsequent studies in different contexts would be helpful for understanding the external validity of these results. For example, Spain is particularly generous to immigrants in terms of healthcare access relative to many other immigrant-receiving countries, and this may shape the strength of the relationship between legal status and trafficking. In addition, policymakers would benefit from a better understanding of the relative costs and benefits of drug-specific enforcement policies as compared to immigration policies in combating illegal trafficking.

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Table 1: Effect of Immigrants on Drug Trafficking (OLS)

	Outcome: Confiscated Imports Dummy			
	(1)	(2)	(3)	(4)
Log immigrants 2011	0.220*** (0.0393)	0.187*** (0.0213)	0.205*** (0.0465)	0.137*** (0.0221)
Observations	5564	5564	5564	5564
	Outcome: Confiscated Exports Dummy			
	(1)	(2)	(3)	(4)
Log immigrants 2011	0.0952*** (0.0214)	0.120*** (0.0192)	0.0671** (0.0220)	0.0696** (0.0216)
Observations	5564	5564	5564	5564

Notes: The table presents OLS estimates of equation 1 at the country-province level. Standard errors are clustered by nationality in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: First Stage Regressions

	Log immigrants 2011			
	(1)	(2)	(3)	(4)
Predicted immigration, 1991-2001	0.149*** (0.0325)		0.154*** (0.0331)	0.353*** (0.0392)
Predicted immigration, 2001-2011		0.0559*** (0.0189)	0.0370* (0.0203)	0.151*** (0.0490)
(Predicted immigration, 1991-2001) ²				-0.00895*** (0.00142)
(Predicted immigration, 2001-2011) ²				0.00228 (0.00194)
(IV 1991-2001)×(IV 2001-2011)				-0.00348* (0.00204)
Observations	5564	5564	5564	5564
R^2	0.687	0.693	0.698	0.740
Country FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Ln dist.	Y	Y	Y	Y
1st-stage F-statistic	21.1	8.8	11.5	152.4

Notes: The table presents coefficient estimates from first-stage regressions at the country-province level. All regressions control for province and nationality fixed effects as well as log distance. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effect of Immigrants on Drug Trafficking (IV)

	Dummy for drug confiscations	
	(1) Imports	(2) Exports
Log immigrants 2011	0.163*** (0.0455)	0.0579* (0.0348)
Observations	5564	5564
Country FE	Y	Y
Province FE	Y	Y
Ln dist.	Y	Y
1st-stage F-statistic	152.4	152.4

Notes: The table presents coefficient estimates from IV regressions of equation 1 at the country-province level. I instrument for *Log immigrants 2011* using $\{IV_{o,d}^D = I_{o,-a(d)}^D \times I_{-c(o),d}^D / I_{-c(o)}^D\}_{1991-2001, 2001-2011}$, their interaction across decades, and squared terms as the excluded instruments. The dependent variable is a dummy for whether any drugs trafficked between country o and province d were confiscated between 2011 and 2016 (imports into Spain in column 1 and exports out of Spain in column 2). All regressions control for province and nationality fixed effects as well as log distance. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Effect of Immigrants on Drug Trafficking (PPML)

	Value of drug confiscations			
	(1) Imports	(2) Imports	(3) Exports	(4) Exports
Log immigrants 2011	0.732*** (0.212)	0.481* (0.249)	0.0411 (0.275)	0.644* (0.350)
First-stage residuals		0.386 (0.252)		-0.712* (0.385)
Observations	3224	3224	2728	2728
Country FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Ln dist.	Y	Y	Y	Y
1st-stage F-statistic		152.4		152.4

Notes: The table presents coefficient estimates from pseudo-Poisson maximum likelihood estimation at the country-province level. I instrument for *Log immigrants 2011* using $\{IV_{o,d}^D = I_{o,-a(d)}^D \times I_{-c(o),d}^D / I_{-c(o)}^D\}_{1991-2001, 2001-2011}$, their interaction across decades, and squared as the excluded instruments. The dependent variable is the value of illegal drug confiscations between country o and province d between 2011 and 2016. I implement a control function approach using Poisson pseudo-maximum likelihood estimation whereby I estimate residuals from a first-stage regression of all the instruments on *Log immigrants 2011*, and then include that residual as a control in the second-stage regression as in columns 2 and 4. All regressions control for province and nationality fixed effects as well as log distance. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effect of Immigrants on Drug Confiscations: Extensive Margin

	Imports Confiscations (Dummy)		Exports Confiscations (Dummy)	
	(1)	(2)	(3)	(4)
Log immigrants 2011	0.163*** (0.0455)	0.0837* (0.0461)	0.0579* (0.0348)	0.0418 (0.0335)
Observations	5564	4642	5564	5125
R^2	0.047	0.027	0.019	0.016
Country FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Ln dist	Y	Y	Y	Y
1st-stage F-statistic	152.4	372.5	152.4	165.4
Sample	All	< 15000 USD predicted confiscations		All < 15000 USD predicted confiscations

Notes: The table presents coefficient estimates from IV regressions of equation 1 at the country-province level. I instrument for the immigrant population measure using $\{IV_{o,d}^D = I_{o,-a(d)}^D \times I_{-c(o),d}^D / I_{-c(o)}^D\}_{1991-2001, 2001-2011}$, their interaction across decades, and squared terms as the excluded instruments. In column 2, I subset to the set of country-province pairs for which predicted import confiscations (defined in equation 13) fall below \$15,000; I do the same for predicted export confiscations in column 4. Standard errors are clustered by nationality in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Effect of Immigrants on Illegal Drug Activity (Province Panel)

	(1)	(2)	(3)	(4)	(5)
	First-Stage: Log immigrants	2SLS: Log value imports confiscated	2SLS: Log native-born used drugs last 12 mo.	2SLS: Log native-born ever used drugs	2SLS: Log native-born drug trafficking arrests
Ethnic Enclave IV	0.178*** (0.0412)				
Log immigrant population		21.59* (11.61)	2.030 (2.195)	4.546 (3.222)	-7.056 (13.60)
Observations	728	728	310	312	364
First-stage F-statistic	18.8	18.8	4.5	4.4	0.7
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates from IV regressions of equation 14 at the province-year level. I instrument for *Log immigrants* using the excluded instrument defined in equation 15, with the first-stage shown in column 1. In column 2, the dependent variable is the log of 1 plus the value of illegal drug imports confiscated. The dependent variable of columns 3 and 4 is the log number of native-born Spaniards reporting to the EDADES survey that they used drugs in the last 12 months (column 3) or ever (column 4). The dependent variable of column 5 is the number of Spanish citizens arrested for illegal drug trafficking. Standard errors are clustered at the autonomous community-by-year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Effect of Immigrants on Cannabis Cultivation (Province Cross-Section)

	(1) First-stage: Log immigrants 2011	(2) 2SLS: Log cannabis plants seized
Ethnic Enclave IV	0.355*** (0.0800)	
Log immigrant population		1.775*** (0.353)
Observations	50	50
R^2	0.695	0.559
1st-stg. F-stat	19.7	19.7
Dep. var. mean (unlogged)	9.3e+04	4003

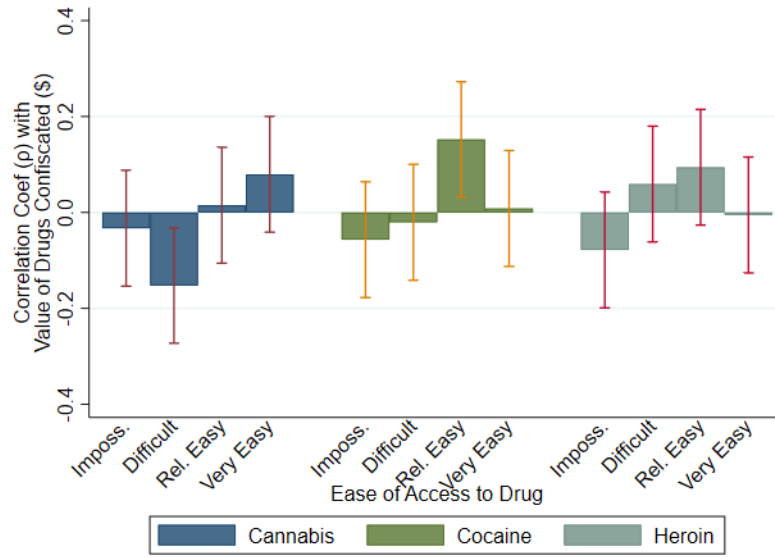
Notes: The table presents coefficient estimates from IV regressions of equation 16 at the province level. I instrument for *Log immigrants 2011* using the excluded instrument defined in equation 15, with the first-stage shown in column 1. In column 2, the dependent variable is the log of the number of individuals with Spanish nationality arrested for drug trafficking offenses. I control for the 1981 province population. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Effect of Immigrants by Legal Status on Drug Confiscations

	Dummy for Any Drug Confiscations	
	Imports	Exports
Log regular immigrants 2011	0.0911 (0.0606)	0.157*** (0.0421)
Log irregular immigrants 2011	0.152** (0.0730)	-0.171*** (0.0602)
Observations	5200	5200
SW 1st-stg. F-stat. (regular immigrants)	63.8	63.8
SW 1st-stg. F-stat. (irregular immigrants)	18.8	18.8

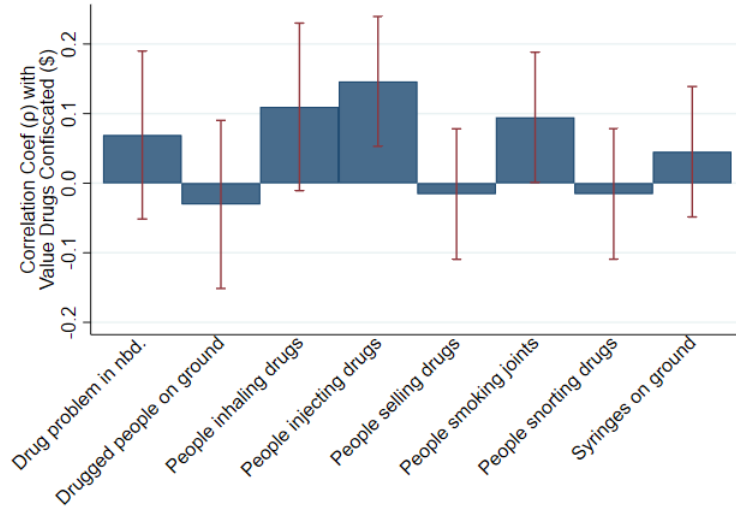
Notes: The table presents estimates of IV regressions by legal status at the country-province level. The dependent variable is a dummy for whether any confiscation has occurred, separately for imports (column 1) and exports (column 2). I instrument for the immigrant population by legal status using 19 as well as the interaction across decades and squared terms. Standard errors are clustered by country in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Correlation of Drug Confiscations to Drug Availability by Drug



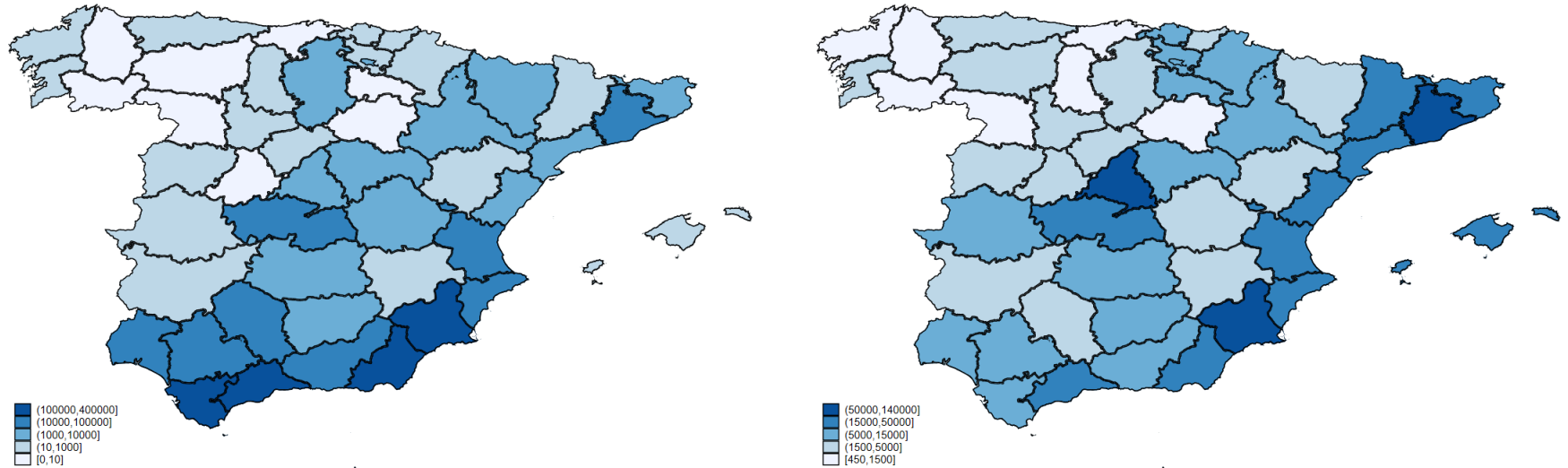
Notes: This figure shows Pearson correlation coefficients between the amount of confiscations per capita of a particular drug with the fraction of respondents in a province who report finding it impossible/difficult/relatively easy/very easy to obtain that drug within 24 hours averaged over the 2011, 2013, and 2015 waves of the EDADES (Suvey on Alcohol and Drugs in Spain) survey. Amphetamines were not asked about until the 2013 survey, and are thus excluded. Ninety percent confidence intervals are shown in red. The sample is a cross-section of 52 Spanish provinces.

Figure 2: Correlation of Drug Confiscations to Subjective Impressions of Local Drug Availability



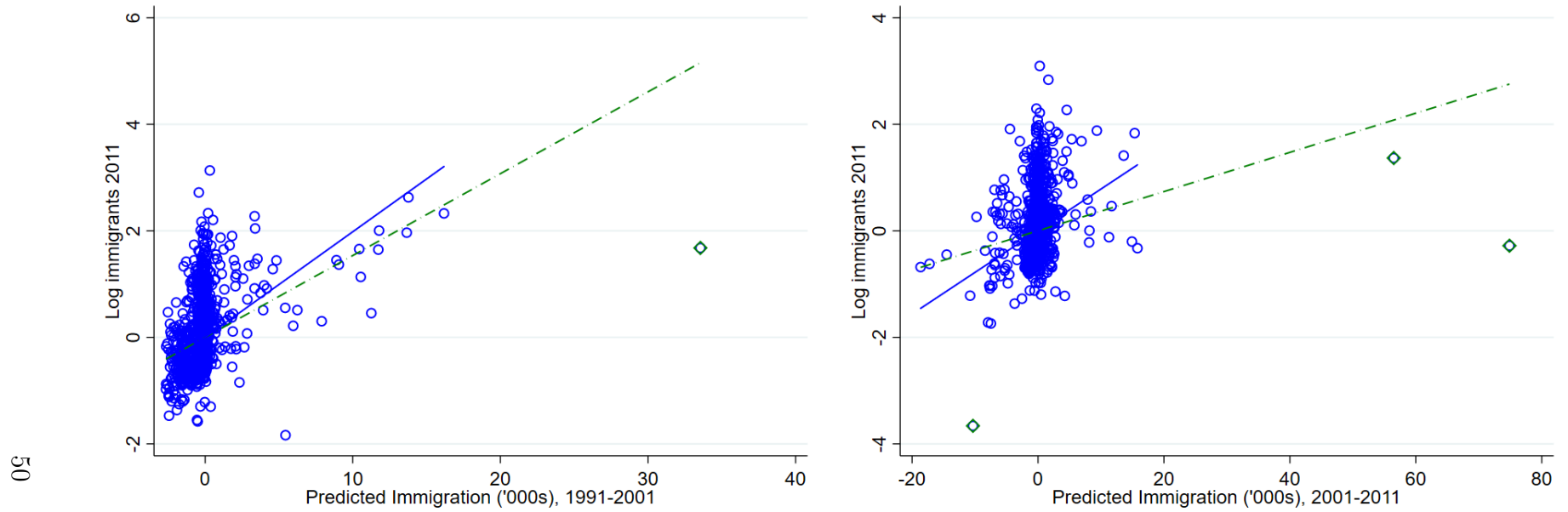
Notes: This figure plots Pearson correlation coefficients between illegal drug confiscations (measured in dollars) per capita across all drugs with the fraction of respondents in the province who reported observing the listed drug-related behaviors either “frequently” or “very frequently” or, for the first bar on the left, “very.” The behaviors listed are, from left to right: (i) “Thinking about where you live, how important of a problem do you think illegal drugs are?”; (ii) “How often in your neighborhood are there drugged people on the ground?”; (iii) “How often in your neighborhood are there people inhaling drugs in paper/aluminium?”; (iv) “How often in your neighborhood are there people injecting drugs?”; (v) “How often in your neighborhood are there people selling drugs?”; (vi) “How often in your neighborhood are there people smoking joints?”; (vii) “How often in your neighborhood are there people snorting drugs by nose?”; (viii) “How often in your neighborhood are there syringes lying on the ground?” I drop cannabis from the drug confiscation variable in the correlations for the questions on people snorting or injecting drugs or syringes being on the ground, since cannabis is generally not snorted or injected. 90% confidence intervals are shown in red. Correlations estimated on a cross-section of 52 Spanish provinces, pooled across 2011 to 2016 for drug confiscations and across the 2011, 2013, and 2015 waves of the EDADES for the drug availability survey measures.

Figure 3: Drug Confiscations and Immigrant Population: The Case of Morocco and Cannabis
 Cannabis Confiscations (kg) Number of Moroccan Immigrants



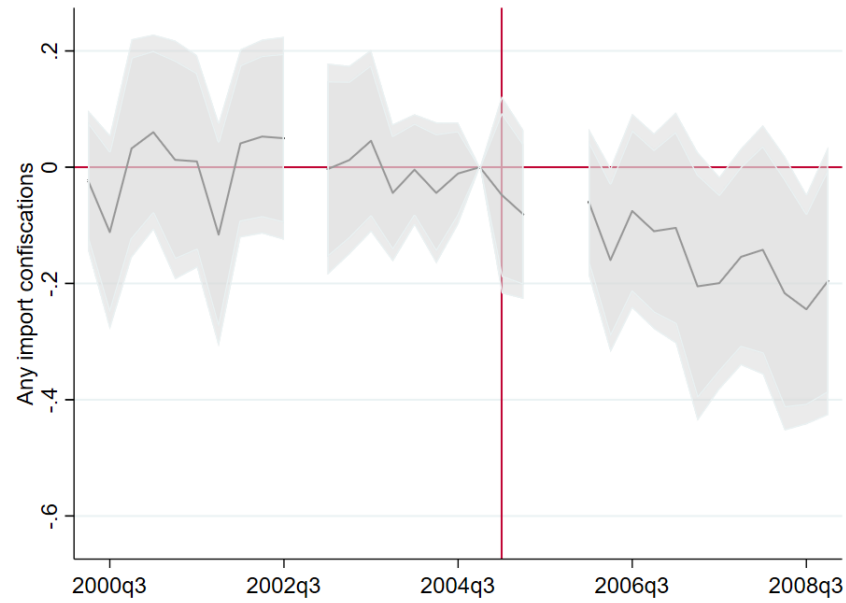
Notes: The figure on the left shows the distribution across Spanish provinces of cannabis confiscations between 2011 and 2016 originating from Morocco; the figure on the right shows the distribution across Spanish provinces of the number of individuals with Moroccan nationality in 2011.

Figure 4: First-Stage Fit



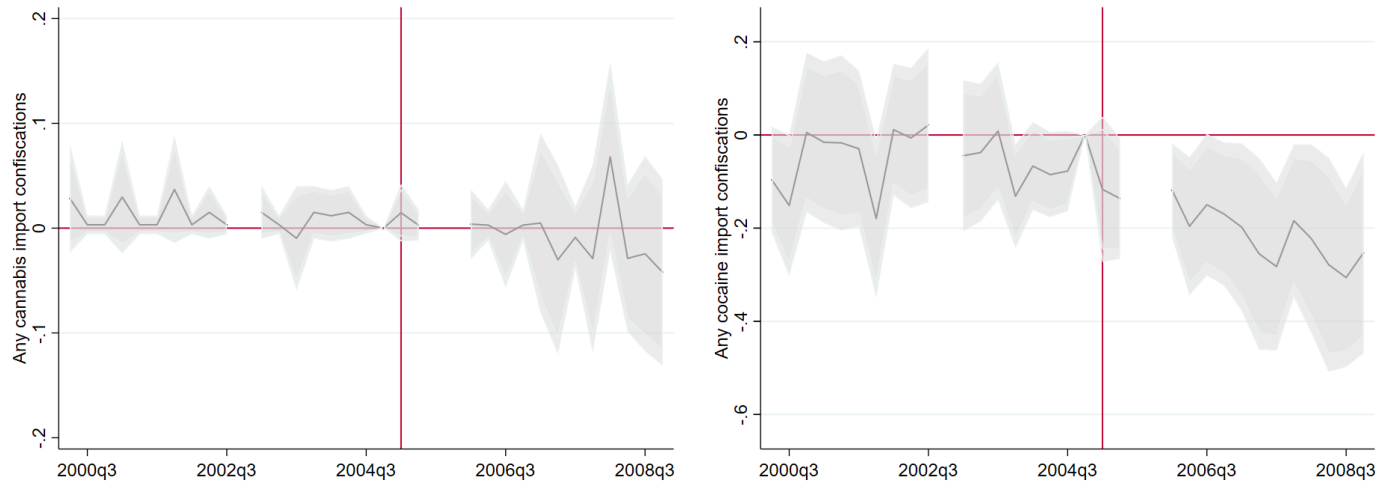
Notes: The figure shows the conditional scatter plots of *Log immigrants* 2011 with the instruments for immigrant inflows for decades 1991 to 2001 (on the left) and 2001 to 2011 (on the right). Both *Log immigrants* 2011 and the predicted inflows are residualized on origin and destination fixed effects, log distance, and on the instrument from the left-out decade. I plot the regression line both with (green diamonds, dashed green line) and without (blue circles, blue solid line) outliers.

Figure 5: Effect of 2005 Immigrant Regularization on Drug Imports



Notes: The figure shows an event study plot of the effect of the 2005 immigrant regularization on whether any drug imports were confiscated locally . Plot is estimated using equation 20. The light grey area shows the 90% confidence interval while the darker grey area shows the 90% confidence interval.

Figure 6: Effect of 2005 Immigrant Regularization on Confiscations by Drug Type



Notes: The figure shows event study plots of the effect of the 2005 immigrant regularization on confiscations of cannabis (on the left) and cocaine (on the right). The dependent variable is whether any of the drugs were confiscated coming from the origin country in that year. Plots are estimated using equation 20. The light grey area shows the 90% confidence interval while the darker grey area shows the 90% confidence interval.

Appendix

A Theory

In this section I briefly lay out a theoretical justification for the bilateral- and province-level regressions discussed above. This theory allows me to provide a structural interpretation to the estimated coefficients from Section 3.

Setup. Illegal drug varieties are indexed by $\omega \in [0, 1]$ with region d 's efficiency in producing variety ω denoted as $z_d(\omega)$. Aggregate consumption of illegal drugs in province d is defined as

$$C_d = \left[\int_0^1 q_d(\omega)^{(\eta-1)/\eta} d\omega \right]^{\eta/(\eta-1)} \quad (21)$$

for elasticity of substitution $\eta > 0$ and the quantity of each drug variety $q_d(\omega)$. Following [Eaton and Kortum \(2002\)](#), I assume region d 's production efficiency distribution is Frèchet

$$F_d(z) = e^{-T_d z^{-\theta}} \quad (22)$$

where $T_d > 0$ and $\theta > 1$ and Z_d has a geometric mean $\exp(\gamma/\theta) T_d^{1/\theta}$ where γ is Euler's constant.

In terms of prices, the cost of good ω produced in o and delivered to d is the realization of the random variable

$$P_{od} = \frac{w_o \tau_{od}}{Z_o}$$

for average input wages w_o and bilateral trade costs $\tau_{o,d} \geq 1$ (with $\tau_{dd} = 1$ for all d).

Gravity. Denote by $X_{o,d}$ the flow of illegal drugs from origin country o to destination d . Then I have the gravity equation

$$\ln X_{o,d} = \delta_o + \delta_d + \theta \ln \tau_{o,d}$$

where for bilateral immigrant population $M_{o,d}$,

$$\ln \tau_{o,d} = \alpha_0 \ln t_{o,d} - \alpha_1 \ln M_{o,d} \quad (23)$$

where $t_{o,d}$ are bilateral trade costs when the bilateral immigrant population is zero. Hence, we have

$$\ln X_{o,d} = \delta_o + \delta_d + \theta\alpha_0 \ln t_{o,d} - \theta\alpha_1 \ln M_{o,d}$$

In practice, bilateral trade costs (when the bilateral immigrant population is zero) can be expressed as

$$\ln t_{o,d} = f(\text{gravity}_{o,d}) + \tilde{\varepsilon}_{o,d}$$

where $f(\text{gravity}_{o,d})$ incorporates the standard bilateral gravity variables—geographic or cultural closeness—and $f(\cdot)$ is a standard functional form. Hence, we obtain our estimating equation

$$\ln X_{o,d} = \delta_o + \delta_d + f(\text{gravity}_{o,d}) + \beta_2 \ln M_{o,d} + \varepsilon_{o,d} \quad (24)$$

where $\varepsilon_{od} \equiv \theta\alpha_0\tilde{\varepsilon}_{o,d}$ and the same applies for $f(\cdot)$ and where $\beta_2 \equiv -\theta\alpha_1$. The unobservable bilateral links that shape trade flows, captured by $\varepsilon_{o,d}$, also shape bilateral migration. Hence, estimating (24) using OLS will yield a biased estimate of β_2 (the combination of the trade elasticity and the impact of migration on trade costs). However, with a valid instrument, we can estimate this combination.

Consumption. Following Eaton and Kortum (2002), I have

$$C_d = \frac{1}{\gamma} \left(\frac{T_d}{\pi_{d,d}} \right)^{\frac{1}{\theta}} \quad (25)$$

where the share of imports to d coming from o is

$$\pi_{od} = \frac{T_o(w_o\tau_{o,d})^{-\theta}}{\sum_{o'} T_{o'}(w_{o'}\tau_{o',d})^{-\theta}}$$

Assuming $\tau_{d,d} = 1$, I have that

$$\pi_{dd} = \frac{T_d(w_d)^{-\theta}}{\sum_o T_o(w_o\tau_{o,d})^{-\theta}} \quad (26)$$

Combining the equations 25 and 26,

$$C_d = \frac{1}{\gamma} w_d \left(\sum_o T_o(w_o\tau_{o,d})^{-\theta} \right)^{\frac{1}{\theta}}$$

We are interested in understanding the impact of a small change in the vector $\{M_{od}\}_o$ on consumption in d . We assume that $dT_o = 0$ for all $o \neq d$. Log differentiating the previous

expression yields

$$d \ln C_d = d \ln w_d + \frac{\pi_{d,d}}{\theta} d \ln T_d - \sum_o \pi_{o,d} d \ln (w_o \tau_{o,d})$$

Now assuming that d is a small economy such that $dw_o = 0$ for all $o \neq d$, we obtain

$$d \ln C_d = (1 - \pi_{d,d}) d \ln w_d + \frac{\pi_{d,d}}{\theta} d \ln T_d - \sum_{o \neq d} \pi_{o,d} d \ln \tau_{o,d}$$

Starting from the previous expression, substituting in equation 23 for $d \ln \tau_{o,d}$ to obtain

$$d \ln C_d = (1 - \pi_{d,d}) d \ln w_d + \frac{\pi_{d,d}}{\theta} d \ln T_d - \sum_{o \neq d} \pi_{o,d} (\alpha_0 d \ln t_{od} - \alpha_1 d \ln M_{o,d})$$

and setting $d \ln t_{od} = 0$ (i.e., assuming no change in the impact of time-invariant gravity variables) yields

$$d \ln C_d = (1 - \pi_{d,d}) d \ln w_d + \frac{\pi_{d,d}}{\theta} d \ln T_d + \alpha_1 \sum_{o \neq d} \pi_{o,d} d \ln M_{o,d} + \varepsilon_d$$

where $\varepsilon_d \equiv -\alpha_0 \sum_{o \neq d} \pi_{o,d} d \ln \tilde{\varepsilon}_{o,d}$.

To obtain a cross-sectional estimating equation comparable to what I estimate at the province level, I integrate up to obtain

$$\begin{aligned} \ln C_d - B_0 &= (1 - \pi_{d,d})(\ln w_d + B_1) + \frac{\pi_{d,d}}{\theta}(\ln T_d + B_2) + \alpha_1 \sum_{o \neq d} \pi_{o,d}(\ln M_{o,d} + B_o) + \int \varepsilon_d \\ \ln C_d &= (1 - \pi_{d,d}) \ln w_d + \frac{\pi_{d,d}}{\theta} \ln T_d + \alpha_1 \sum_{o \neq d} \pi_{o,d} \ln M_{o,d} + \left(\frac{B_2}{\theta} - B_1\right) \pi_{d,d} + \alpha_1 \sum_{o \neq d} B_o \pi_{o,d} + \epsilon_{od} \end{aligned}$$

Consider the case of cocaine, where there is no domestic production; that is, $T_d = 0$, which implies $\pi_{d,d} = 0$. Then we have

$$\ln C_d = \ln w_d + \alpha_1 \sum_{o \neq d} \pi_{o,d} \ln M_{o,d} + \alpha_1 \sum_{o \neq d} B_o \pi_{o,d} + \tilde{\epsilon}_{od}$$

Finally, to relate consumption as defined in equation 25 to empirically observed measures of drug consumption \tilde{C}_d , I assume

$$\ln C_d = -\rho_0 + \rho_1 \ln \tilde{C}_d$$

Then we have

$$\ln \tilde{C}_d = \rho_0 + \frac{1}{\rho_1} \ln w_d + \frac{\alpha_1}{\rho_1} \sum_{o \neq d} \pi_{o,d} \ln M_{o,d} + \frac{\alpha_1}{\rho_1} \sum_{o \neq d} B_o \pi_{o,d} + \tilde{\epsilon}_{o,d}$$

B Additional Empirical Analyses

B.1 2004 Madrid Bombing Event Study

I also explore the short-run effects of a major event in Spain: the 2004 Madrid train bombings. Carried out by a Moroccan immigrant and funded by drug trafficking, the bombings killed 193 people, injured about 2,000, and were a major international news story. Due to the connection between the bombings and Moroccan drug trafficking, enforcement intensity directly specifically at Moroccan smuggling may have suddenly increased, while the number of Moroccan immigrants (in the short-run) changed only minimally.

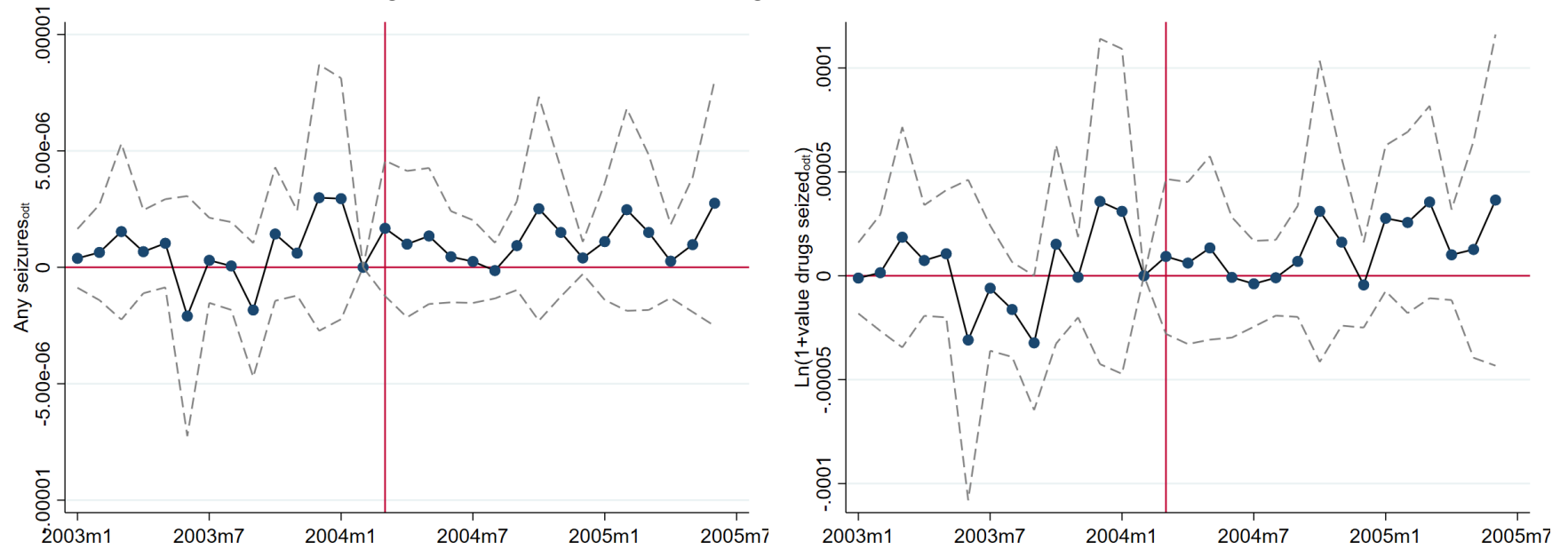
To assess whether this change in enforcement intensity caused a notable increase in drug confiscations, I estimate

$$Y_{o,d}^t = \alpha_{o,d} + \alpha^t + \sum_{t \neq \text{Mar. 2004}} \theta^t \times M_{Morocco,d}^{2003} + \epsilon_{o,d}^t$$

where $o \in \{Moroccan, non - Moroccan\}$, d is a Spanish province, t denotes year-month, and $Y_{o,d}^t \in \{\ln(C_{o,d}^t + 1), \mathbf{1}\{C_{o,d}^t > 0\}\}$. The vector $\{\theta^t\}$ will capture the extent to which the number of Moroccan immigrants induces larger changes in enforcement intensity.

I plot the event study graphs in Figure 7 and find no statistically significant structural break in confiscations. One caveat for this approach is that the same pattern may result if drug traffickers also suddenly change their trafficking behavior and routes to avoid increased enforcement intensity.

Figure 7: Effect of 2005 Bombing on Confiscations from Morocco



Notes: This figure shows event study plots of the effect of the 2004 Madrid train bombings on confiscations of drugs coming from Morocco. I control for year-month and province-by-origin fixed effects, where origins are aggregated into two groups: Moroccan or non-Moroccan. The year-month coefficients plotted are interacted with the number of Moroccan immigrants present in the province in 2003.

C Additional Tables and Figures

Table 9: Effect of Immigrants on Drug Trafficking by Origin Drug-Hubness

	Drug Confiscations Dummy 2011-2016			
	(1)	(2)	(3)	(4)
	Imports	Exports	Imports	Exports
Log immigrants 2011	0.126** (0.0543)	0.0528 (0.0389)	0.674*** (0.205)	0.245*** (0.0844)
Log immigrants 2011 \times % of seized drugs from o	1.377*** (0.299)	-0.192 (0.159)		
Log immigrants 2011 \times Drug hubness rank			-0.00138*** (0.000338)	-0.000409** (0.000168)
Observations	5564	5564	5564	5564
R^2	0.054	0.018	0.071	0.006
Country FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Ln dist	Y	Y	Y	Y
1st-stage F-statistic	132.0	132.0	41.6	41.6

Notes: The table presents coefficient estimates from IV regressions of equation 1, modified to include a term interacting *Log immigrants 2011* with a measure of the immigrants' origin country drug-hubness, either the fraction of confiscated drugs worldwide originating in the country or the ordinal rank of that fraction. I instrument for *Log immigrants 2011* using the IV defined in equation 3 and the IV interacted with the measure of drug hubness, as well as the IVs interacted across decades and squared. The dependent variable is a dummy for whether any illegal drugs imported from country o were confiscated in province d between 2011 and 2016 in columns 1 and 3, and a dummy for confiscated exports in columns 2 and 4. All regressions control for nationality and province fixed effects as well as log distance. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Robustness to Different Functional Forms

	Drug Confiscations 2011-2016 (Dummy)					
	(1) Import	(2) Export	(3) Import	(4) Export	(5) Import	(6) Export
Log immigrant population (2001)	0.203*** (0.0607)	0.0920* (0.0495)				
$\ln \left(\frac{M_{o,d}^{2011}}{1000} \right)$ (-1 for ∞)			0.118*** (0.0282)	0.0362 (0.0243)		
$(M_{o,d}^{2011})^{1/3}$					0.0224*** (0.00774)	0.00946* (0.00511)
Observations	5564	5564	5564	5564	5564	5564
Country FE	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
Ln dist	Y	Y	Y	Y	Y	Y
1st-stage F-statistic	290.2	290.2	17.1	17.1	388.2	388.2

Notes: The table presents coefficient estimates from IV regressions at the country-province level using different functional forms to measure bilateral immigrant population. I instrument for the immigrant population measure using $\{IV_{o,d}^D = I_{o,-a(d)}^D \times I_{-c(o),d}^D / I_{-c(o)}^D\}_{1991-2001, 2001-2011}$, their interaction across decades, and squared terms as the excluded instruments. The dependent variable is a dummy for whether any drugs trafficked between country o and province d were confiscated between 2011 and 2016 (either or imports or exports). All regressions control for province and nationality fixed effects as well as log distance. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Effect of Immigrants on Drug Confiscations (GMM)

Drug Smuggling	
β^{Import}	0.191*** (0.045)
π	0.017 (0.022)
β^{Export}	0.143*** (0.070)
Observations	5564

Notes: The table presents coefficient estimates from nonlinear GMM estimation of equation 5. Standard error for π not adjusted for the constraint that the log function does not accept nonpositive arguments. See section 3.9.1 for additional details. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Gravity Specification: Alternative Standard Errors

	(1) Imports (dummy)	(2) Exports (dummy)
Log immigrants 2011	0.163	0.0579
Cluster by country	(0.0455)	(0.0348)
Heteroskedasticity Robust	(0.0242)	(0.0277)
Cluster by province	(0.0241)	(0.0244)
2-way cluster by country & province	(0.0454)	(0.0322)

Notes: The table presents coefficient estimates and various standard errors from IV regressions of equation 1 at the country-province level. I control for nationality and province fixed effects as well as log distance. *Log immigrants 2011* is instrumented with the leave-out push-pull IV from equation 3. I cluster by country in my baseline specification.

Table 13: Effect of Immigrants on Drug Trafficking: Panel Analysis

	Drug Confiscations Dummy 2011-2016			
	(1)	(2)	(3)	(4)
	Imports	Imports	Exports	Exports
Log immigrant population	0.185*** (0.0121)	0.304*** (0.0905)	0.0453*** (0.00786)	0.120* (0.0676)
Observations	74984	74984	74984	74984
Log distance	Y	Y	Y	Y
Origin-Year FE	Y	Y	Y	Y
Dest.-Year FE	Y	Y	Y	Y
Origin-Province FE	N	Y	N	Y
1st-stage F-statistic	747.8	32.2	747.8	32.2

Notes: The table presents estimates of equation 6 in columns 1 and 3 and equation 7 in columns 2 and 4 at the country-province-year level. I instrument for the immigrant population using predicted flows defined in equations 8 (for columns 1 and 3 only) and 9 as well as their second-order interactions and squared terms. Standard errors are clustered by nationality-year in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14: Effect of Immigrants on Legal Trade

	Value of Legal Trade	
	(1)	(2)
	Imports	Exports
Log immigrants 2011	-0.0173 (0.0567)	-0.0840* (0.0445)
Residuals	0.105 (0.0780)	0.193*** (0.0428)
Observations	5136	5136
Country FE	Y	Y
Province FE	Y	Y
Ln dist.	Y	Y
1st-stage F-statistic	152.4	152.4

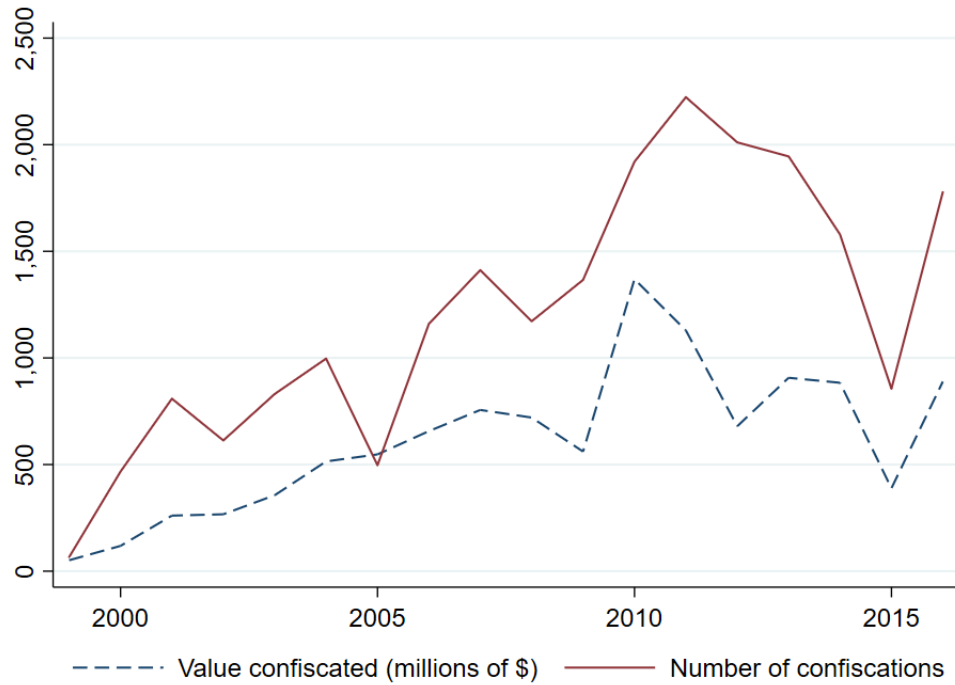
Notes: The table presents coefficient estimates from PPML regressions at the country-province level. The dependent variable is the value of legal trade summed over the year 2011 through 2016 as reported from the ADUANAS-AEAT database (imports into Spain in column 1 and exports out of Spain in column 2). All regressions control for province and nationality fixed effects as well as log distance. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15: Effect of Immigrants on Illegal Drug Activity: Province Panel with Leave-Out Instrument

	(1)	(2)	(3)	(4)	(5)
	First-Stage: Log immigrants	2SLS: Log value imports confiscated	2SLS: Log native-born used drugs last 12 mo.	2SLS: Log native-born ever used drugs	2SLS: Log native-born drug trafficking arrests
Shift-Share IV	0.157*** (0.0412)				
Log immigrant population		22.79* (13.25)	2.430 (2.599)	5.316 (4.045)	-9.809 (22.76)
Observations	728	728	310	312	364
First-stage F-statistic	14.6	14.6	3.5	3.5	0.4
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

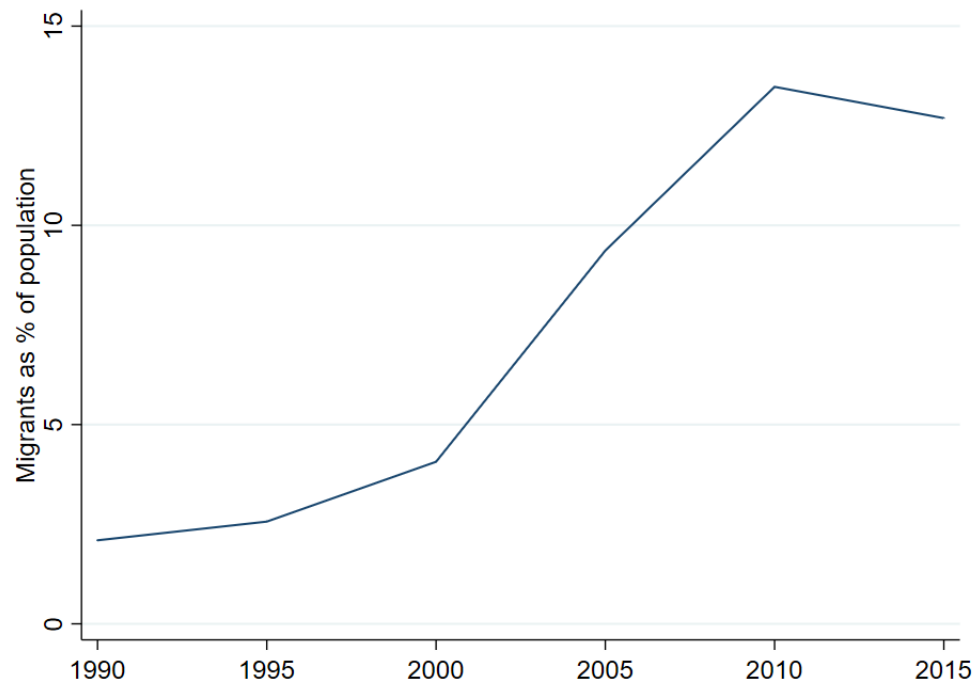
Notes: The table presents coefficient estimates from IV regressions of equation 14 at the province-year level. I instrument for *Log immigrants* using the excluded instrument defined in equation 15, with the first-stage shown in column 1. In column 2, the dependent variable is the log of 1 plus the value of illegal drug imports confiscated. The dependent variable of columns 3 and 4 is the log number of native-born Spaniards reporting to the EDADES survey that they used drugs in the last 12 months (column 3) or ever (column 4). The dependent variable of column 5 is the number of Spanish citizens arrested for illegal drug trafficking. Standard errors are clustered at the autonomous community-by-year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 8: Illegal Drug Confiscations per Year, 1999-2016



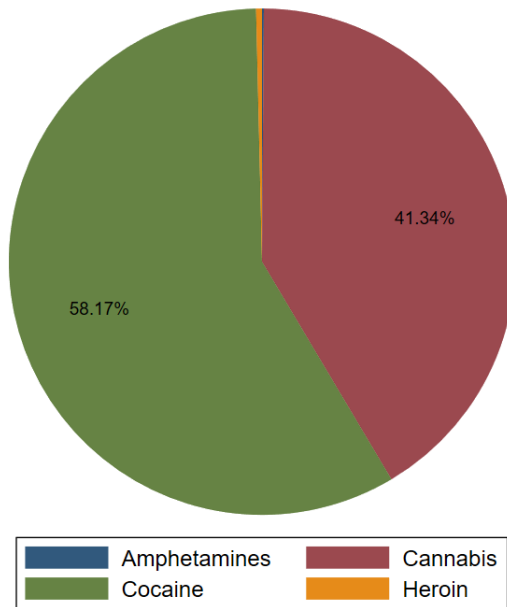
Notes: This figure shows the value of drugs trafficked from foreign countries confiscated over time by Spanish authorities and the number of confiscation events as reported to the United Nations Office of Drugs and Crime (UNODC). Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure 9: Immigrant Population Share in Spain, 1990–2015



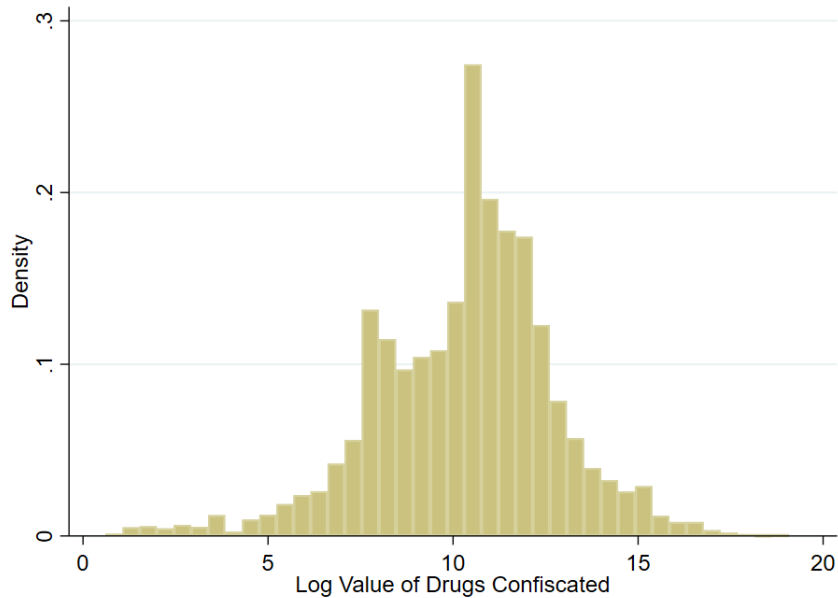
Notes: This figure shows the fraction of the Spanish population born in another country over time. The data are reported by the World Bank but originally come from the United Nations Population Division.

Figure 10: Confiscations by Drug Type



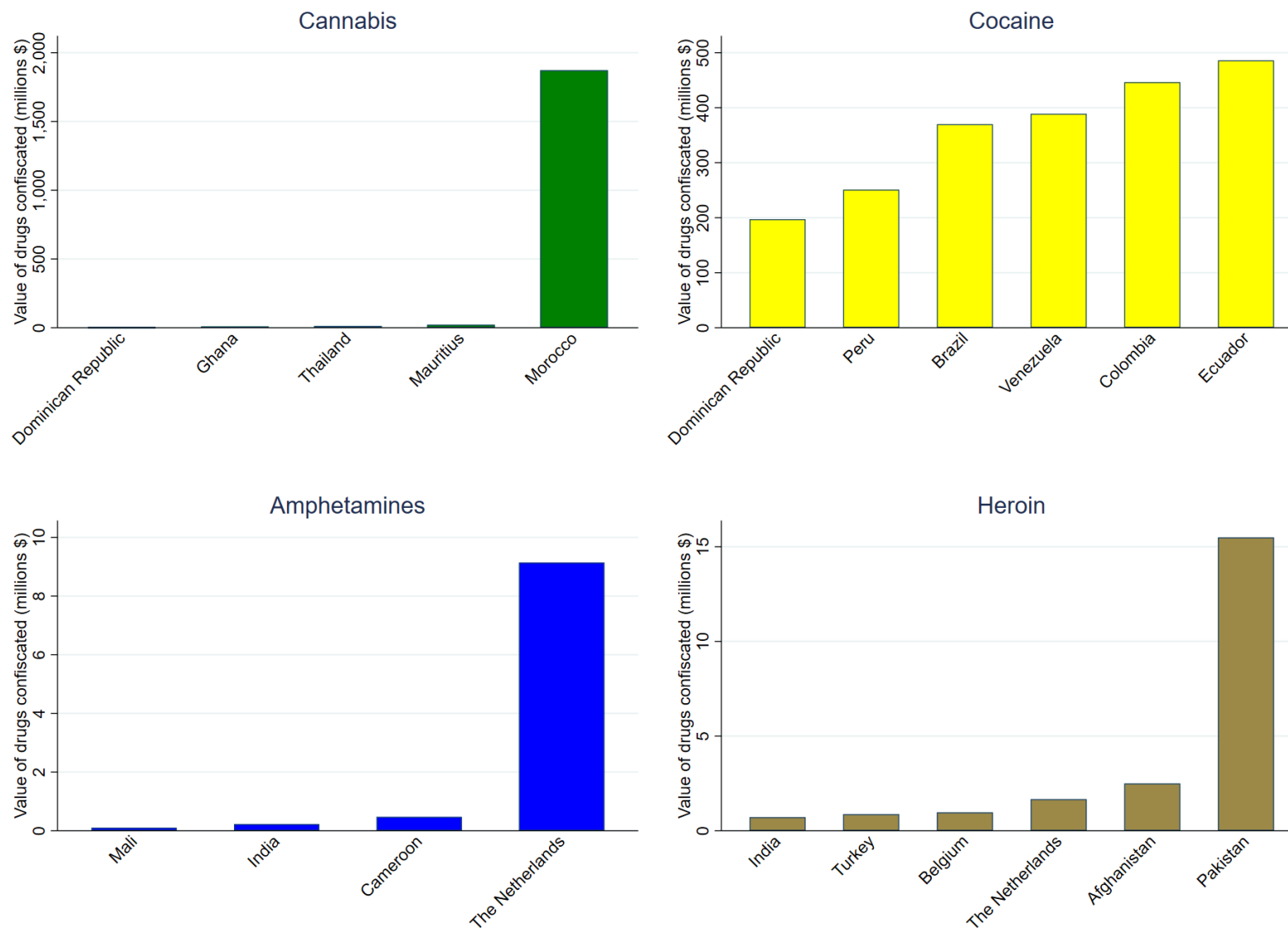
Notes: This figure shows the makeup of drug confiscations in Spain by drug type. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the United Nations Office of Drugs and Crime (UNODC).

Figure 11: Distribution of Log Value of Confiscations



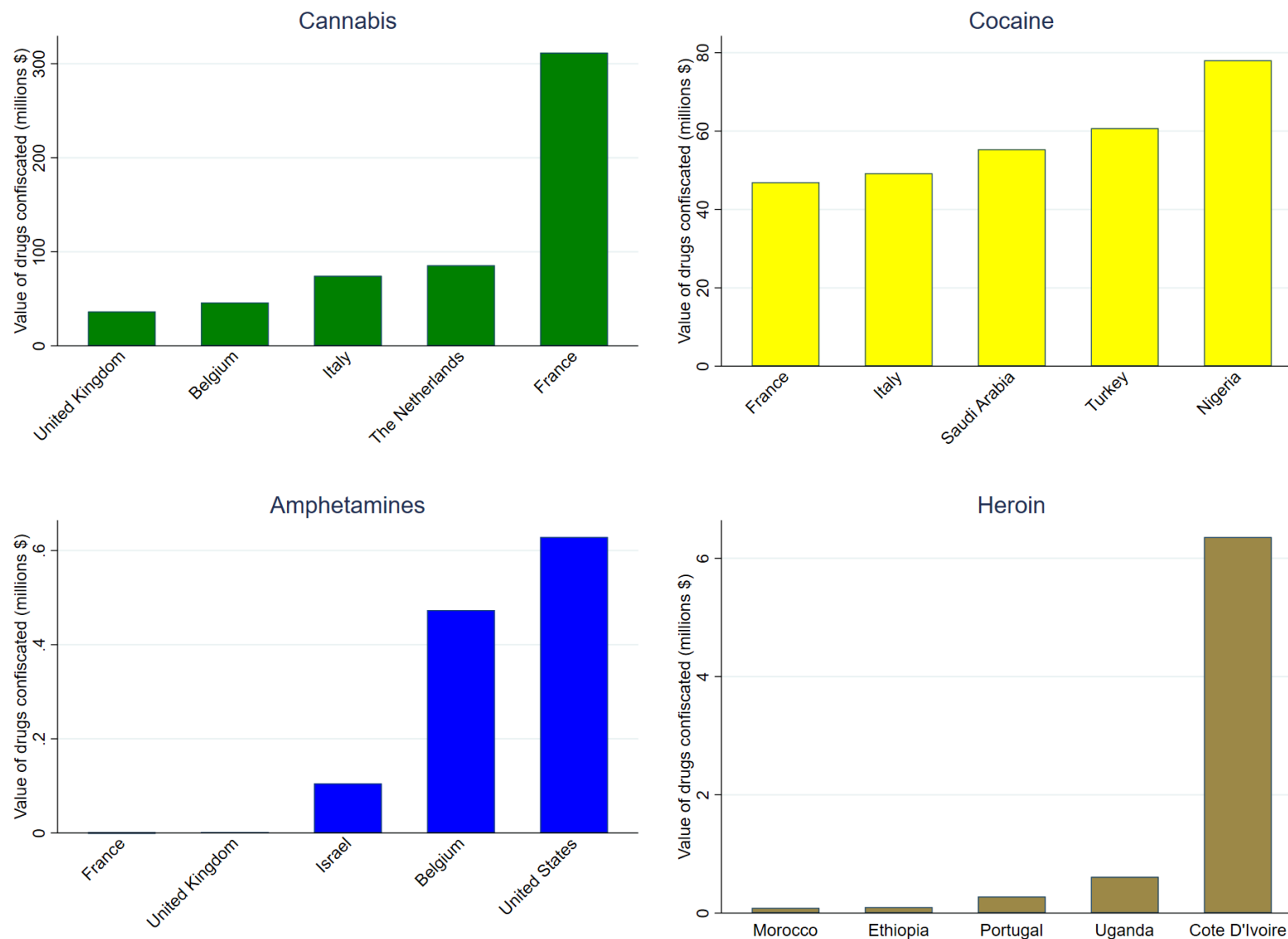
Notes: This figure shows the distribution of the log value of drug confiscations in Spain between 2011 and 2016 as reported to the United Nations Office of Drugs and Crime (UNODC). Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure 12: Top Five Origins by Drug



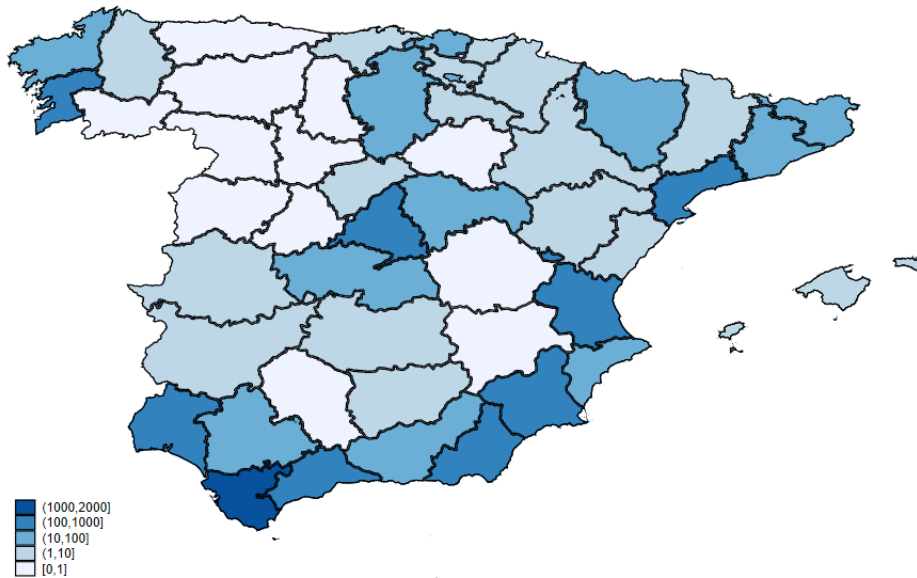
Notes: This figure shows the top five countries of origin of illegal drugs confiscated in Spain between 2011 and 2016 by drug. Source: United Nations Office of Drugs and Crime (UNODC)

Figure 13: Top 5 Intended Destinations by Drug



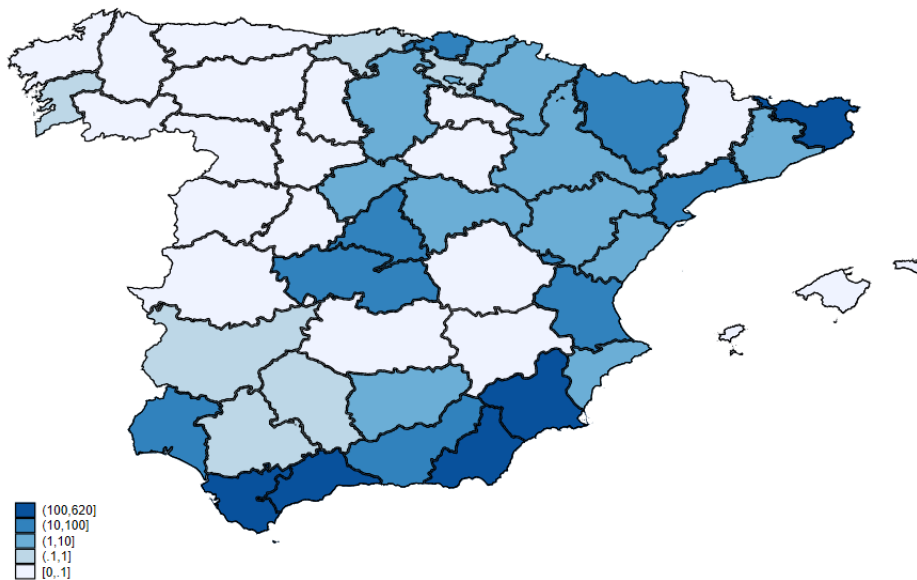
Notes: This figures shows the top five countries of intended destination of illegal drugs confiscated in Spain between 2011 and 2016. Source: United Nations Office of Drugs and Crime (UNODC)

Figure 14: Geography of Drug Import Confiscations in Spain
Imports



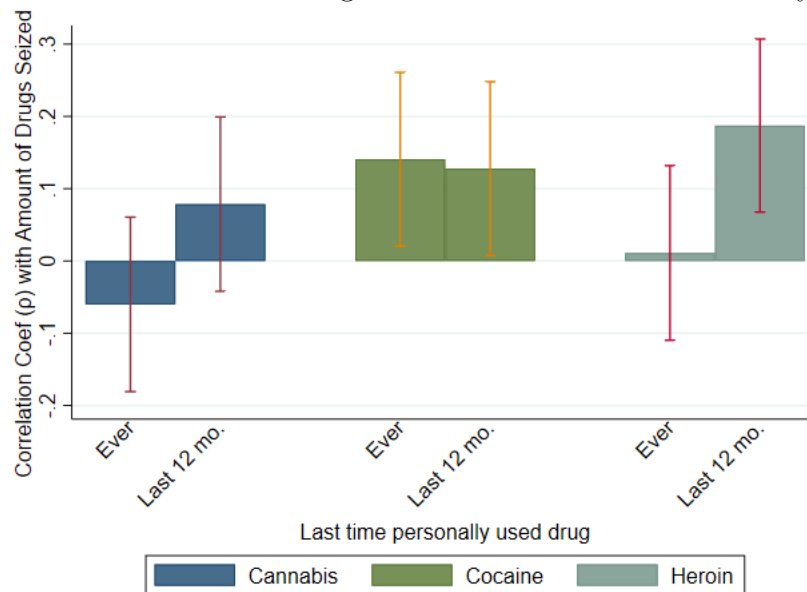
Notes: This figure shows the distribution of drug confiscations of imports (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office of Drugs and Crime.

Figure 15: Geography of Drug Confiscations Intended for Export in Spain
Exports



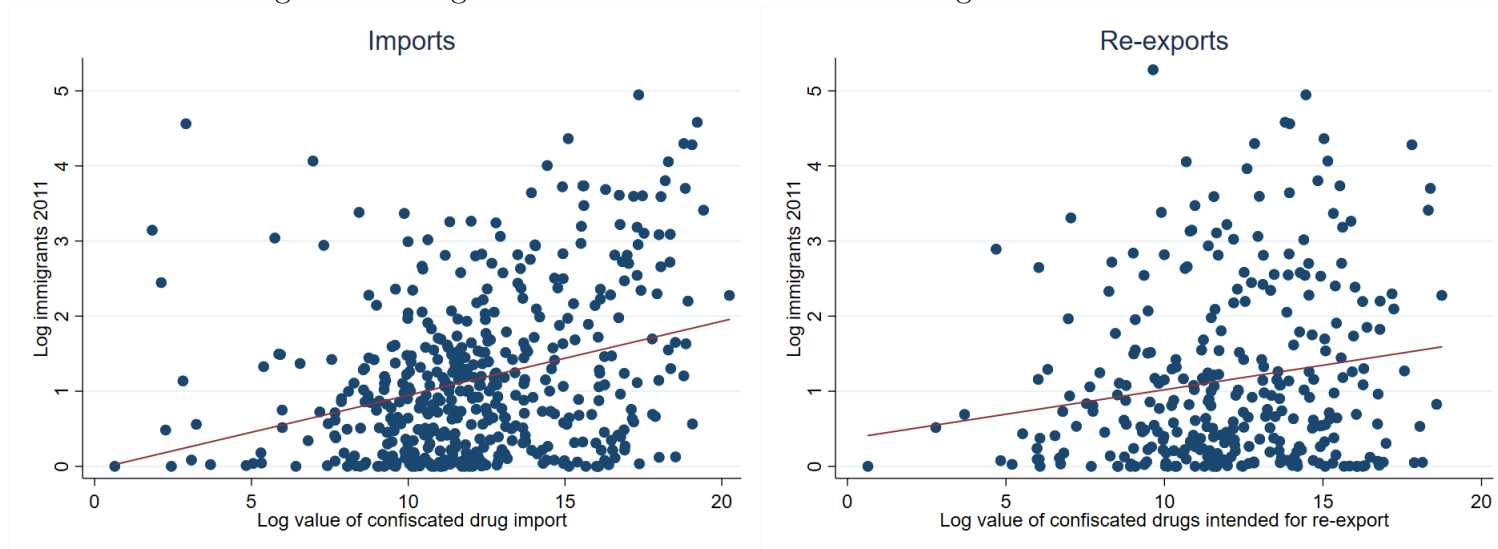
Notes: This figure shows the distribution of confiscations of drugs intended for export (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office of Drugs and Crime.

Figure 16: Correlation of Drug Confiscations to Personal Use by Drug



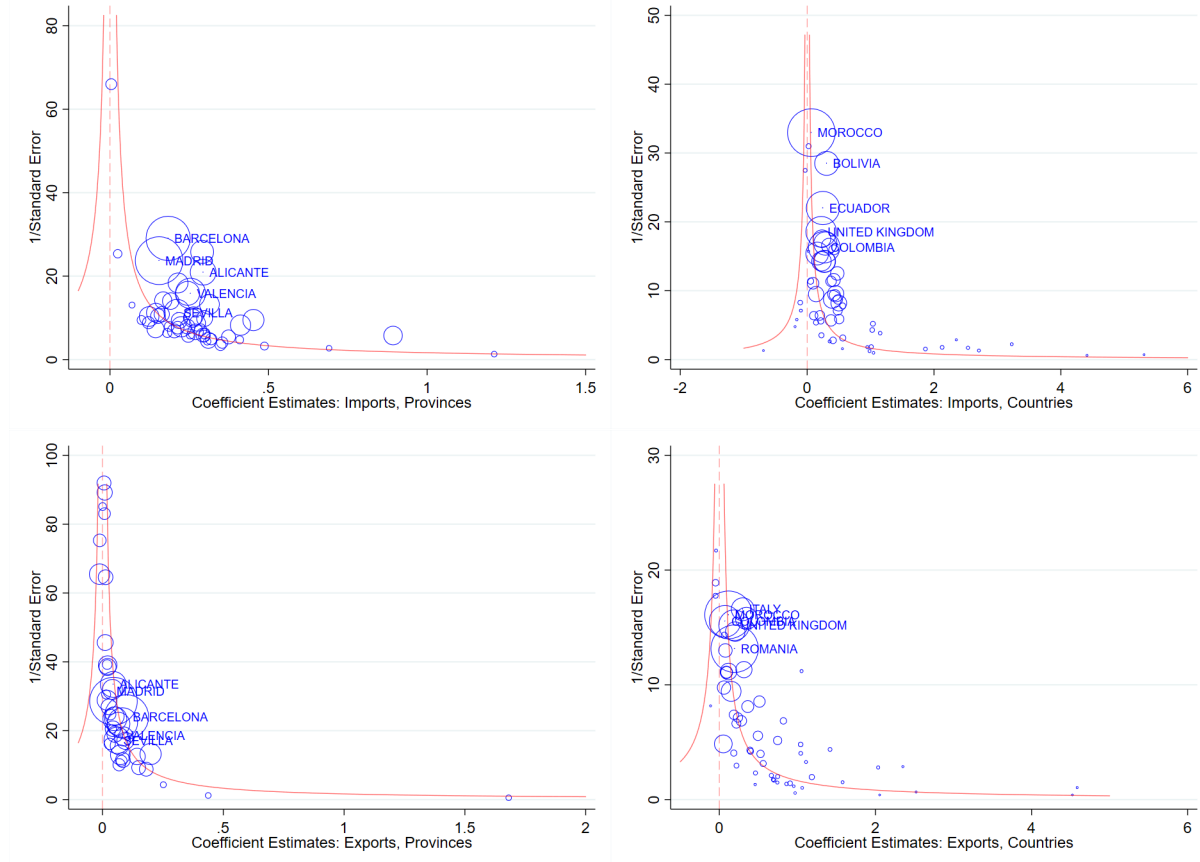
Notes: This figure shows the correlation coefficient between the amount confiscated per capita for each drug with the fraction of respondents in a province who report having ever used the drug or having used the drug within the last 12 months averaged over the 2011, 2013, and 2015 waves of the EDADES (Survey on Alcohol and Drugs in Spain). Amphetamines were not asked about until the 2013 survey and are thus excluded. Ninety percent confidence intervals are shown in red. The sample is a cross-section of 52 Spanish provinces.

Figure 17: Drug Confiscations and Number of Immigrants Raw Correlation



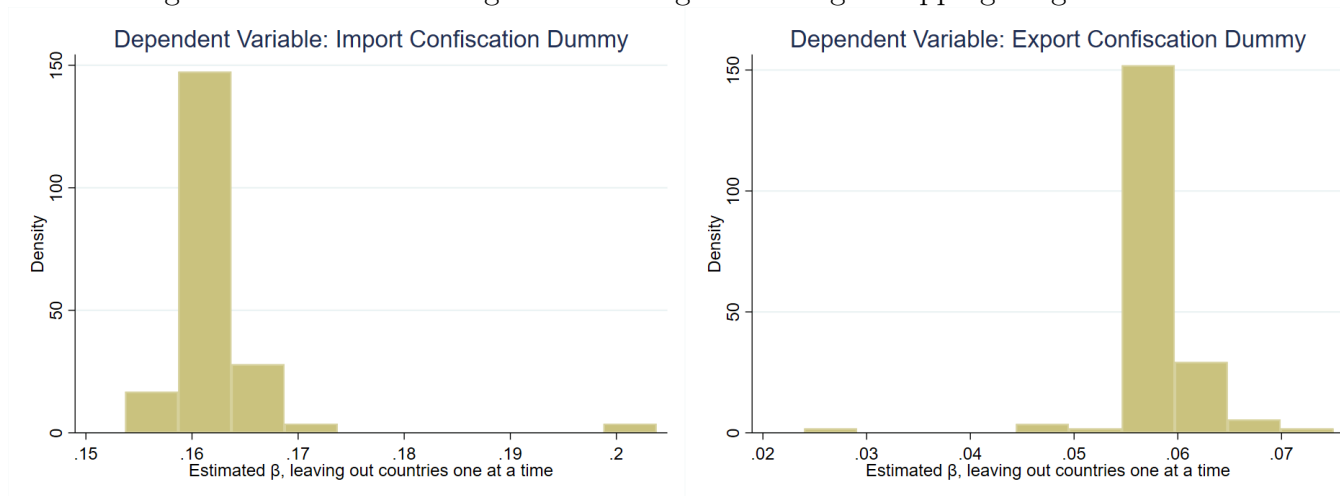
Notes: The figure on the left shows the scatter plot of the bilateral log value of confiscated drug imports on the x-axis with the bilateral log number of immigrants measured in 2011 on the y-axis. The figure on the right is the same but plots the log of the value of drugs confiscated intended for re-export on the x-axis.

Figure 18: Heterogeneous Effect of Immigrants on Drug Trafficking by Country and Province



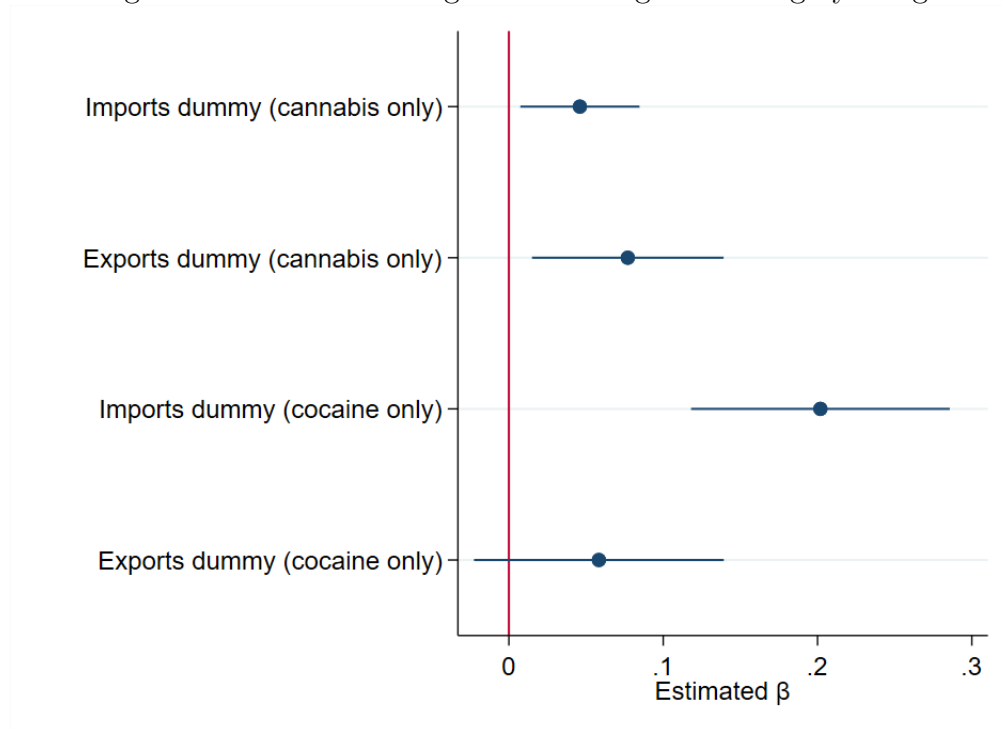
Notes: This figures shows funnel plots of the estimated coefficients and inverse standard errors from 2SLS regressions of drug trafficking dummies (imports in top charts; exports in bottom charts) on *Log Migrants* 2011, controlling for log distance between the immigrants' origin country and Spanish province, and subsampled separately to each Spanish province and origin country. Circle sizes represent the province population (left-hand charts) or the number of immigrants in Spain from the origin country (right-hand charts). The x-axis is the coefficient estimate, and the y-axis is the inverse of the standard error of that estimate. The curve plots $y = \pm 1.65/x$; hence, circles above this curve are statistically significant at the 10% level. I separately drop countries or provinces for which I observe no import or export confiscations. For readability, I drop China in the top right chart and Ukraine in the bottom right chart, which are both major outliers, though both statistically indistinguishable from zero.

Figure 19: Effect of Immigrants on Drug Trafficking: Dropping Origin Countries



Notes: The figures show the distribution of the estimated effect of immigrants on illegal drug confiscations (β from equation 1) when leaving out one nationality at a time. The figures show the distribution of β s when the dependent variable of equation 1 is a dummy for whether any drug trafficking (imports on the left and exports on the right) from a given origin country was confiscated locally between 2011 and 2016. The figure on the

Figure 20: Effect of Immigrants on Drug Trafficking by Drug



Notes: The figure shows IV estimates of the effect of immigrants on drug trafficking (β from equation 1) for the two major drugs trafficked in Spain: cocaine and cannabis (see Figure 10).

Figure 21: Binscatter, Any Import Confiscation on Bilateral Immigrant Population

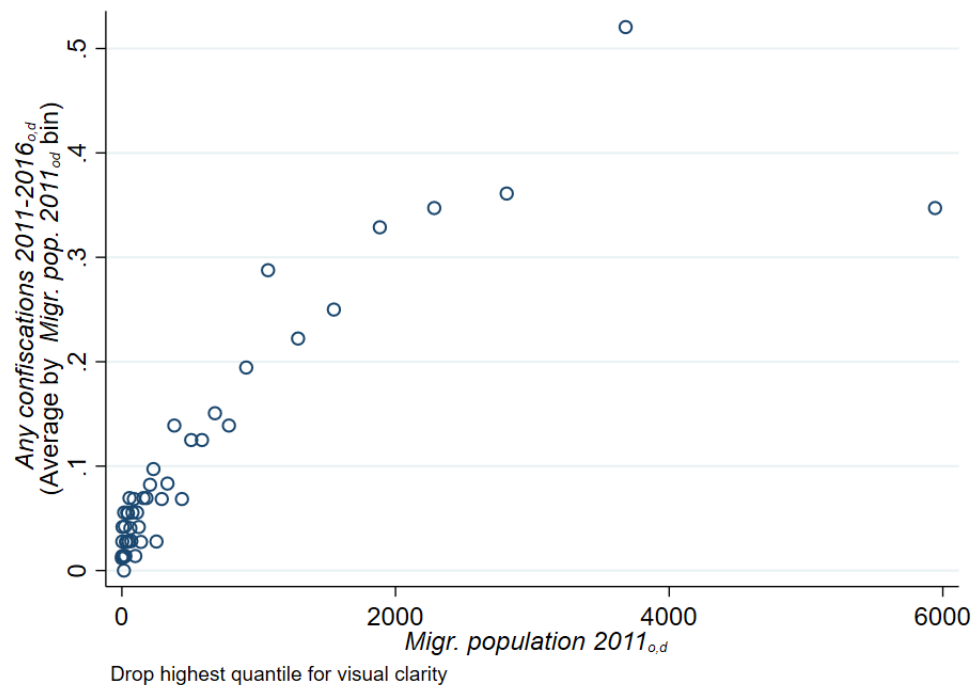
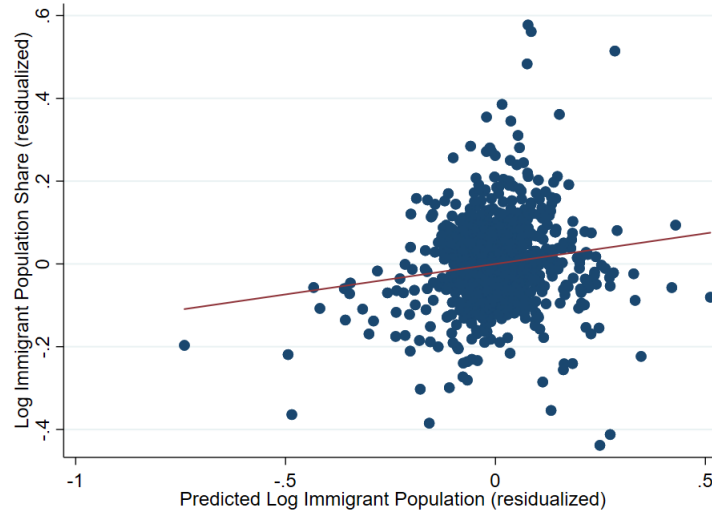


Figure 22: First-Stage Fit, Province-Level Panel



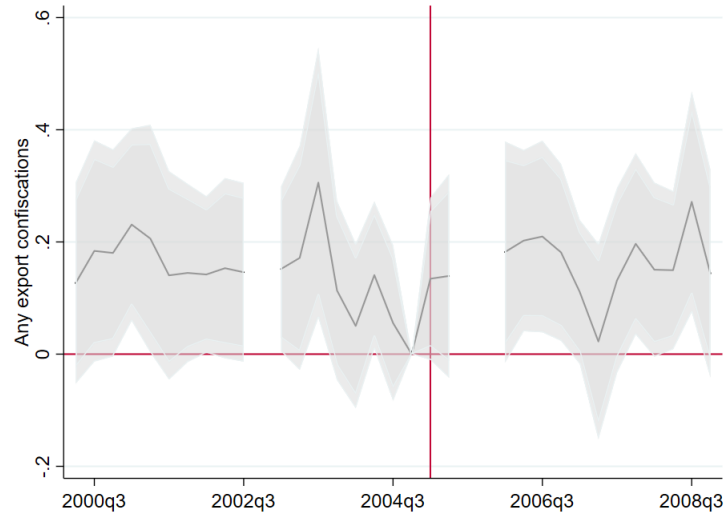
Note: The figure shows the first-stage fit of province immigrant population on the province-level shift-share instrumental variable defined in equation 15, both residualized on year and province fixed effects.

Figure 23: Immigrant Work Permit Issuance



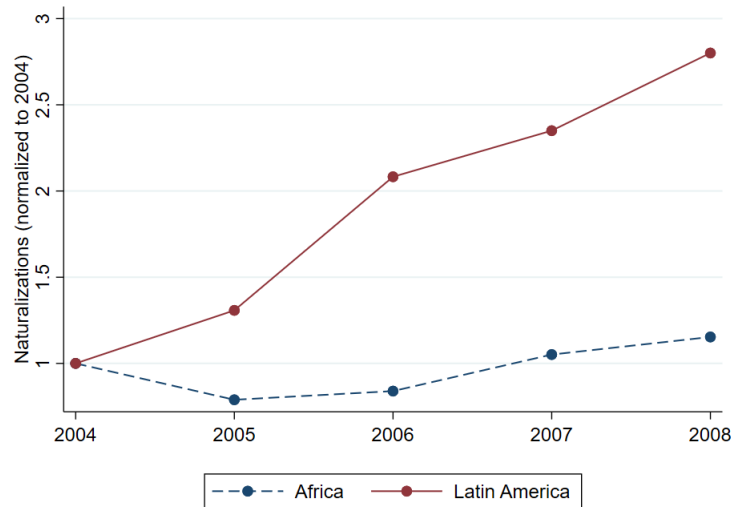
Notes: The figure shows times series of the number of residency permits granted to immigrants.

Figure 24: Effect of 2005 Immigrant Legalization on Illegal Drug Exports



Note: The figure shows event study plots of the effect of the 2005 immigrant regularization on whether any drug exports were confiscated. Plot is estimated using equation 20. The light grey area shows the 90% confidence interval while the darker grey area shows the 90% confidence interval.

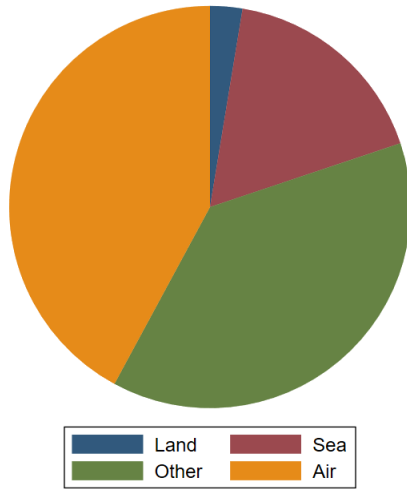
Figure 25: Immigrant Citizenship Acquisition by Continent



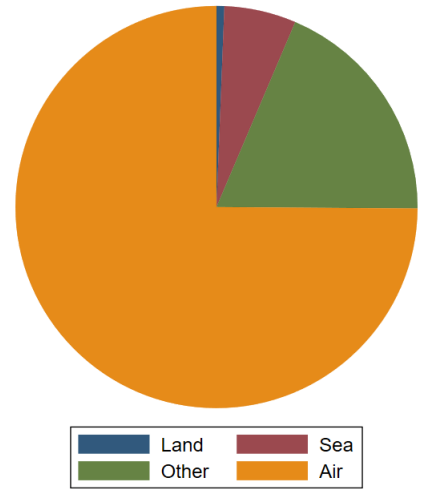
Notes: The figure shows the time series of the number of immigrants obtaining citizenship by continent, for both African immigrants and Latin American immigrants.

Figure 26: Drug Confiscations by Mode of Transport

By Number of Confiscations



By Value of Drugs Confiscated



Notes: The figure shows the shares of mode of transportation of confiscated drugs. On the left I plot fraction of confiscation events, on the right, I plot the share of dollar values confiscated.