Immigrants, Legal Status, and Illegal Trade

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Abstract

Nearly $2 trillion worth of illegal goods are trafficked across international borders every year, generating violence and other social costs along the way. Some have controversially linked illegal trafficking to immigrants, yet an appropriate immigration policy response is unclear. 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 by origin country 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 value of drugs trafficked from the origin country confiscated in a given province by 12%. Moreover, this relationship is driven entirely by immigrants without legal status. 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 long-run decline in drug trafficking, corresponding to the acquisition of citizenship by the immigrants.

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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: illegal drugs. I use novel data on drug confiscations from Spain and exogenous variation in immigrant populations to show that immigrants without legal status have a large positive causal effect on the trafficking of illegal drugs from the immigrants' countries of origin. I find no effect of legal immigration on illegal drug trafficking. Because there may be characteristics of immigrants that shape selection into legal status and into drug trafficking, I estimate the dynamic effects of a mass immigrant regularization policy. I find that granting immigrants legal status results in a long-run decline in drug trafficking, corresponding to immigrants acquiring citizenship.

The main contribution of this paper is to provide the first causally identified estimates of the effect of immigrants on illegal trafficking and the first exploration of mechanisms

[1]Several 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.

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 phenomenons 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. In particular, 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 irregular.

I exploit unique institutional features in Spain that facilitate the measurement of irregular immigrant populations. Unlike the United States and other European countries, immigrants to Spain can obtain healthcare and other government benefits regardless of their legal status in exchange for registering with the 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). In particular, I estimate a gravity equation of illegal drug flows from a given origin country on the number of immigrants from the country living in a given Spanish 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 either law enforcement activity directed towards specific nationalities in Spain (in the case of the country fixed effect) or variation in law enforcement efficacy in confiscating drugs across provinces (in the case of 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, Morrocan immigrants and Moroccan drug traffickers may be drawn to Barcelona for its familiar Mediterranean climate. To address this potential endogeneity, I adapt 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 re-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 the origin country will be confiscated locally by 0.5 percentage points, and raises the market value of confiscated drugs coming from the origin country by 12%. 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 re-export to the immigrants' home country will be confiscated locally by 0.4 percentage points and raises the value of drugs intended for re-export to the immigrants' home country by 7%.

These main results are robust to a range of alternative specifications and sampling choices. I relax the functional form assumption in my baseline specification, separately using non-linear generalized method of moments and non-parametric estimation methods, and find results consistent with my baseline estimation. In addition, no single drug or region drives my baseline result, as I find consistent effects when leaving out individual origins, destinations, and drugs. To gauge the reasonableness of the estimated magnitude, I compare coefficients between a gravity model of illegal trafficking and a gravity model of legal trade and find similar effect sizes.

I argue that immigrants' social connections to their origin country primarily drives the bilateral immigrant-trafficking relationship that I estimate. This is consistent with the qualitative evidence that immigrants reduce information frictions and transaction costs for imports and exports. In addition, I find that immigrants raise re-exports of drugs, a margin where immigrants' demand for drugs should not drive the results. 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 (not production) 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 re-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 origin country and province fixed effects in my baseline specification, this competing explanation must operate at the origin country-by-Spanish province level. I take two approaches to rule out that such enforcement intensity variation drives my baseline results. First, I combine my baseline estimates of the effect of immigrants on drug confiscations with a back-of-the-envelope estimate of the fraction of illegal drugs coming into Spain which are confiscated by the authorities. I find that an implausibly large responsiveness of enforcement intensity to immigration is required to explain my quantitatively large baseline estimates. Second, while in my baseline estimation I assume that enforcement intensity does not co-vary with the immigrant population. I test this assumption by focusing on the extensive margin of drug trafficking. I still 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, do not completely offset the effect of immigrants on trafficking. I assess the strength of these general equilibrium responses by estimating the effect of immigrants on additional 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.

I estimate the effect of immigrants on drug trafficking separately by immigrant legal status using the gravity specification. I find that my baseline estimates are driven entirely by irregular immigrants. To achieve causal identification, 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 share of immigrants from the country and outside the region of the province back in 2003.

Unobserved immigrant characteristics, such as a propensity for illegal behavior, may drive immigrants into both irregular status and drug trafficking. These differences in the composition immigrants by legal status at the origin 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 and also put regularized immigrants on the path to citizenship. Immigrants are eligible for citizenship after living in Spain continuously and legally for a number of years depending on their country of origin.

I find that the 2005 mass immigrant regularization program reduced drug trafficking significantly shortly after immigrants became eligible to become Spanish citizens, but not before. The lack of an immediate effect of regularization on drug trafficking is consistent with Pinotti (2017), as the program-eligible immigrants had pre-existing attachments to the formal labor market.A back-of-the-envelope calculation leveraging the gravity estimates suggests that an alternative policy in which regularization was not conditional on pre-existing attachment to the formal labor market would have reduced drug confiscations by as much as 20 percent.

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 several 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 implement. 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

[2] See, 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).

market opportunities available to immigrants (Bell et al., 2013; Spenkuch, 2014; Pinotti, 2017; Freedman et al., 2018). I also show the potential for long-run effects of immigrant legalization, in part due to immigrant naturalization, whereas prior work focuses on short-run effects.

I also expand upon the literature on the economics of illegal trade by studying the trafficking of illegal drugs, one of the most consequential of illegally smuggled goods.[3] I follow a strand of mostly theoretical papers on the economics of smuggling (Bhagwati and Hansen, 1973; Grossman and Shapiro, 1988; Thursby et al., 1991). In more recent work, Fisman and Wei (2009) empirically study the smuggling and mis-invoicing of cultural goods, and Akee et al. (2014) estimates the determinants of human trafficking.

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. Section 4 discusses enforcement intensity and general equilibrium responses, and Section 5 discusses the role for immigration policy. 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

[3]A 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., 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.

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

[5]UNODC (p. 30, 2020a).

[6]UNODC (p. 67, 2020a).

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 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 network[9], 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 A.10, 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

[7] UNODC (p. 71-73, 2020a).

[8] See 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)

[10] For example, "L-15 [a convicted drug trafficker] was from Ghana. In 2000 he was approached by a Ghanian 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)

[11] For 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)

[12] Irregular immigrants who enter Spain via either crossing the Strait of Gibralter 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).

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 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 comitting 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,

[13]The 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.

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

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 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

[15] Specifically, 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.

[16] Reporting 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 A.9) 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.

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 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 A.11. Second, the distribution of drug confiscation amounts is right skewed as shown in Figure A.12, 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 A.13, and Spain re-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 A.15 and A.16.

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

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

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 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 A.17. 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

[18] I 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 iwthin 24 hours.

[19] Respondents 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.

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.

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 A.18. 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. Given complete information on illegal drug flows, I would estimate a gravity equation of the form

$$\ln(X_{o,d}) = \alpha_o + \alpha_d + \beta M_{o,d} + \delta \ln(Dist_{o,d}) + \tilde{\varepsilon}_{o,d}$$

where α_o and α_d are origin and destination fixed effects, respectively, and $Dist_{o,d}$ is the distance in kilometers between o and d taken from Peri and Requena-Silvente (2010).[20] $M_{o,d}$ is a measure of the number of immigrants from o living in d, usually defined as the log of one

[20] I provide microfoundations for this gravity equation in Appendix A.

plus the number of immigrants in d from o, measured in thousands (my results are robust to this functional form choice, as I show in Section 3.8.1). The error term $\tilde{\varepsilon}_{o,d}$ includes all omitted bilateral forces that may shape drug trafficking. I measure the immigrant population $M_{o,d}$ using the 2011 Spanish Census distributed by Minnesota Population Center (2019).

Because I cannot observe actual drug trafficking amounts, I instead use confiscations of illegal drugs. I denote the value of drugs confiscated in province d and coming from origin country o as $C_{o,d}$, where

$$C_{o,d} = E_{o,d} X_{o,d} \tag{1}$$

I define actual drug flows by value from origin country o to province d as $X_{o,d}$ and bilateral enforcement intensity as $E_{o,d} \in [0, 1]$, both of which are unobserved.

Plugging equation 1 into the gravity equation, I obtain my baseline specification,

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

where $\varepsilon_{o,d} = \tilde{\varepsilon}_{o,d} + \ln(E_{o,d})$. The main parameter of interest is β, which measures the responsiveness of illegal drug confiscations to changes in the immigrant population.

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 $M_{o,d}$ is independent of country-province-specific enforcement intensity $E_{o,d}$ and any other country-province-level confounder $\tilde{\varepsilon}_{o,d}$.

For the empirical analysis, I replace the dependent variable $\ln C_{o,d}$ with $\ln(1 + C_{o,d})$ to avoid dropping bilateral links with no confiscations, as these make up more than half of my sample. I also estimate the immigrant-trafficking relationship using a dummy for whether any confiscation occurred as a dependent variable. Because drug confiscations are conducted locally, and therefore reporting practices may vary at the local level, I cluster standard errors at the province level.

In addition to imports, I explore how immigrants affect the re-exports of illegal drugs. Looking at both import and export margins allows me better understand the mechanisms underlying any immigrant-trafficking relationship. For example, if immigrants raise exports than immigrant demand for drugs is unlikely to drive the relationship. To measure intended re-exports, I consider drugs confiscated in d but that were intended to go to country o.[21] As dependent variables $Y_{o,d}$, I use either a dummy for whether any confiscation of drugs intended for re-export occurred $\mathbf{1}\{C_{d,o} > 0\}$ or the log of one plus the value of drugs confiscated and intended for re-export, $\ln(1 + C_{d,o})$.

For the main empirical analysis, my baseline gravity equation is

$$Y_{o,d} = \alpha_o + \alpha_d + \beta M_{o,d} + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d} \tag{2}$$

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 the country and province fixed effects absorb many potential confounders, there may still be unobserved factors at the country-province-pair level, such as the geographic or climatic similarity between a country and a Spanish province. To purge this potential endogeneity from country-province immigrant population, I adapt a leave-out push-pull instrumental variables approach to my setting. Consider, for example, that Moroccan immigrants settling in the province of Alicante may be drawn by 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.

To obtain variation in migration 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.

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

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 Alicante. To do so, we look at the number of Moroccans inflowing into Spain and the number of immigrants from all origin countries inflowing into Alicante for the same decade. In particular, the instrument will predict Moroccans to settle in Alicante if large numbers of immigrants from other countries are also settling there. Similarly, if many immigrants from other origins are settling in Alicante, then an immigrant arriving from Morocco will be predicted to settle in that province.

More specifically, the migration leave-out push-pull instrument interacts the arrival at the national level of immigrants from different origin countries (push) with the attractiveness of different destinations to immigrants (pull) measured by the fraction of immigrants settling in destination d. A simple version of the instrument predicts bilateral immigrant inflows and is defined as

$$\tilde{IV}^{D}_{o,d} = I^{D}_{o} \times \frac{I^{D}_{d}}{I^{D}}, \tag{3}$$

where I^{D}_{o} is the number of immigrants from origin o coming to Spain in decade D, I^{D}_{d} is the number of immigrants from all origins settling in destination province d in decade D, and I^{D} is the total number of immigrants arriving in Spain in decade D.[22]

However, the push-pull instrument defined in equation 3 may still fail the exclusion restriction. This may be the case if bilateral immigration is driven by endogenous confounders such as a similar climate in both origin and destination regions and if bilateral immigration is a large share of the instrument's individual components. Alternatively, there may be spatial correlation in confounding variables. For example, if both Moroccan and Algerian immigrants go to the province of Alicante due to the similar Mediterranean climates, then Moroccan migration to Alicante will be well predicted by Algerian migration so long as Algerian migration to Alicante is a sufficiently large share of total migration to Alicante. However, Algerian and Moroccan migration to Alicante may be jointly predicted by a third factor, climate, which may also affect drug trafficking (e.g., if calm weather facilitates smuggling by sea). 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 defined as

[22] 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.

$$IV_{o,d}^{D} = I_{o,-a(d)}^{D} \times \frac{I_{-c(o),d}^{D}}{I_{-c(o)}^{D}} \tag{4}$$

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.

The identification assumption when using this instrument 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, suppose, immigrants skilled at drug trafficking from Morocco tend to settle in the province of Barcelona and immigrants skilled in drug trafficking from Lebanon settle in Alicante (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 Barcelona and Lebanese are a large fraction of the immigrants settling in Alicante, and therefore materially affect the instrument's prediction of flows of immigrants and drugs from Morocco to Alicante. Then the instrument is predicting bilateral immigration based on a confounding factor: climatic similarity between the immigrants' origin country and the Spanish province.

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 first-stage fit of the instruments for the two decades of predicted inflows. The instruments vary positively with the log number of immigrants, as expected. Column 1 of Table 2 shows the first-stage regression coefficients. Instruments from both decades have a positive and statistically significant coefficient, and the first-stage F-statistic of 23.4 surpasses conventional threshold levels.

3.5 Results

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

Table 2 shows the two-stage least squares estimation results for equation 2 for confiscations of imported drugs. Column 2 shows the results for the extensive margin of drug confiscations. The coefficient estimate of the effect of immigrants on the likelihood of a confiscation of imported illegal drugs for a country-province pair is 0.105 (SE = 0.039). This estimate implies that at the mean immigrant population at the province-country-pair level, 933, a 10% increase in the number of immigrants raises the likelihood that drugs trafficked from the origin country will be confiscated locally by 0.5 percentage points.[23] Similarly, in column 3, the coefficient estimate for the log of the immigrant population on the log value of illegal drugs confiscated is 2.33 (SE=0.56), which implies that a 10% increase in the immigrant population (again, at the province-country-pair level) relative to the mean raises the value of illegal drug imports confiscated by 12%.[24] This increase is in line with some estimates in the literature examining the effect of immigrants on *legal* trade.[25]

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.

Table 3 shows the estimation results when the dependent variable is confiscations of drugs intended for re-export.[26] Column 2 shows the extensive margin result. The coefficient estimate for the effect of immigrants on the likelihood of drugs imported from a given origin country and confiscated locally is 0.083 (SE = 0.021). This estimate implies that at the mean immigrant population, 933, a 10% increase in the number of immigrants raises the likelihood that the link will be used for drug trafficking by 0.4 percentage points.[27] Similarly, in column 3, the coefficient estimate of the log of the immigrant population on the log value

[23] Using $\hat{\beta} = 0.105$ from column 2 in Table 2, can compute: $\mathbb{1}\left[C_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 933\right] = 0.105\left(\ln\left(1 + \frac{933 \times 1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.0049$.

[24] Using $\hat{\beta} = 2.331$ from column 3 in Table 2, we have: $\frac{C_{o,d}^{2011-2016}[M_{o,d}^{2011} = 1.1 \times 933]}{C_{o,d}^{2011-2016}[M_{o,d}^{2011} = 933]} - 1 = \exp\left(2.331\left(\ln\left(1 + \frac{1.1 \times 933}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right)\right) - 1 = 0.116$.

[25] See, for example, Parsons and Vézina (2018), who estimate the effect of a 10% increase in immigrant population raises the value of legal trade by 4.5% to 13.8%.

[26] Column 1 restates the first-stage estimates.

[27] Using $\hat{\beta} = 0.083$ from column 2 in Table 3, can compute: $\mathbb{1}\left[C_{d,o}^{2011-2016} > 0 | M_{o,d}^{2011} = 933\right] = 0.083\left(\ln\left(1 + \frac{933 \times 1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.0039$.

of drugs confiscated is 1.339 (SE=0.34), which implies that a 10% increase in the immigrant population relative to the mean raises the value of drug imports confiscated by 6.5%.[28]

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 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

[28] Using $\hat{\beta} = 1.339$ from column 3 in Table 3, we have: $\frac{C_{d,o}^{2011-2016}[M_{o,d}^{2011}=1.1\times 933]}{C_{d,o}^{2011-2016}[M_{o,d}^{2011}=933]} - 1 = \exp\left(1.339\left(\ln\left(1+\frac{1.1\times 933}{1000}\right) - \ln\left(1+\frac{933}{1000}\right)\right)\right) - 1 = 0.065.$

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 re-export margin. The fact that immigrants increase re-exports suggest that immigrants reduce trade costs rather than simply raise demand for drugs.

3.7 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.[29] I re-estimate equation 2, interacting the country-province immigrant log population with the drug-hub level of the immigrants' origin country.[30]

In Table A.3 I show the estimated coefficients. I find that origin countries that are significantly involved in drug trafficking, that is, send a substantial amount of illicit drugs to countries other than Spain, are more likely to export drugs to Spain when more immigrants from those countries settle in Spain.

3.8 Robustness Checks and Legal Trade

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.

3.8.1 Relaxing Functional Form Assumption

In my baseline specification, equation 2, I measure the endogenous variable of interest as the log of one plus the number of immigrants measured in thousands, $\ln\left(1+\frac{migrants_{o,d}^{2011}}{1000}\right)$. To test whether my results are sensitive to changes in the function form of the endogenous variable, I perform several robustness exercises.

First, I estimate my baseline specification across a range of alternative functional forms for the number of immigrants, including a linear term for the immigrant population. I show

[29] I 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.

[30] Data on world bilateral drug confiscations are similarly taken from the UNODC dataset on individual drug confiscations that I use for Spain. One drawback of these data for countries other than Spain is that reporting of 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.

the results in Tables A.1 and A.2. Across functional forms, more immigrants still lead to more drug confiscations. I also motivate my choice of a log-functional form with the binscatter plot in Figure A.24 of the relationship between the immigrant population and the dummy variable for whether any confiscation occurs at the country-province level.

Next, I relax the log-functional form assumption. Specifically, I estimate

$$\begin{aligned} \mathbf{1}\left[C_{o,d} > 0\right] &= \delta_o + \delta_d + \beta_1 \ln(1 + \pi_1 migrants_{o,d}^{2011}) + \epsilon_{o,d} \\ \ln(C_{o,d}) &= \alpha_o + \alpha_d + \beta_2 \ln(1 + \pi_2 migrants_{o,d}^{2011}) + \varepsilon_{o,d} \end{aligned} \tag{5}$$

In equation 5 I estimate (π_1, π_2) whereas in equation 2 I assume $\pi_1 = \pi_2 = 0.001$. I do so using non-linear generalized method of moments using moment conditions

$$E\left[\boldsymbol{Z_{o,d}} \times (Y_{o,d} - \alpha_o - \alpha_d - \beta_1 \ln(\pi_1 migrants_{o,d}^{2011} + 1))\right] = \mathbf{0}$$

$$E\left[\begin{pmatrix} \boldsymbol{\alpha_o} \\ \boldsymbol{\alpha_d} \end{pmatrix} \times (Y_{o,d} - \alpha_o - \alpha_d - \beta_1 \ln(\pi_2 migrants_{o,d}^{2011} + 1))\right] = \mathbf{0}$$

for dependent variable $Y_{o,d} \in \{\ln(C_{o,d} + 1), \mathbf{1}\left[C_{o,d} > 0\right]\}$ and instrument set

$$\boldsymbol{Z_{o,d}} = \left(I_{o,d}^{IV,1991-2001}, I_{o,d}^{IV,2001-2011}, (I_{o,d}^{IV,1991-2001})^2, (I_{o,d}^{IV,2001-2011})^2\right)'$$

I include squared terms for the instruments to improve convergence and add a moment for the constant, thus yielding 163 moments. Similar to my baseline estimation, I cluster standard errors by province.

Table 4 shows the results. My estimates of (π_1, π_2), do not reject my baseline functional form assumption of $\pi_1 = \pi_2 = \frac{1}{1000}$ and reject the more conventional functional form choice $\pi_1 = \pi_2 = 1$. In addition, the estimates of (β_1, β_2) also are statistically indistinguishable from my baseline coefficient estimates. At the point estimates, I find that a 10% increase in the number of immigrants relative to the mean raises the probability of a confiscation occurring on a bilateral link by 1.1 percentage points and raises the value of illegal drugs confiscated by 20%.

Finally, I relax completely my functional form assumption by estimating a non-parametric regression relating import drug confiscations to the number of immigrants following Chetverikov and Wilhelm (2017). Figure A.21 depicts the results. While I find a weakly increasing relationship between immigrants and import drug confiscations, the standard errors are very large. Nevertheless, I take this as suggestive evidence supporting the baseline parametric estimation results.

3.8.2 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 A.22 shows the distribution of β estimates from equation 2 when I drop one origin country at a time for both dependent variables, $\mathbf{1}\left[C_{o,d} > 0\right]$ and $\ln(C_{o,d} + 1)$. 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 estimate the immigrant-confiscations relationship separately by drug type. For cannabis and cocaine, I estimate positive and statistically significant effect sizes. Cocaine appears to be more reliant on immigrants for importation than cannabis, which can be produced locally in contrast to cocaine, which must be imported. For heroin and amphetamines, the effect is close to zero, as shown in Figure A.23. However, heroin and amphetamines represent less than 1% of drugs confiscated by Spain, as shown in Figure A.11 and therefore precise estimates are difficult to obtain.

Finally, I consider a selection of high-trafficking countries and provinces alone. In Figure A.19, I show the relationship between import drug confiscations and immigrants graphically for Morocco and Colombia and two of the largest receiving provinces, Madrid and Barcelona. In Figure A.20, I do this for re-exports with France and Italy and again with Madrid and Barcelona. In every case, more immigrants lead to more confiscations.

3.8.3 Standard Errors

In my baseline specification, I cluster standard errors at the province level, as this is the level of police reporting of confiscation events. Table A.4 shows estimates using different clustering of standard errors, and they mostly remain statistically significant across the different clustering geographies.

3.8.4 Panel Estimation

In my baseline cross-sectional estimation, I argued that the push-pull instrumental variable dealt with country-province-pair level confounders, such as the similar climate of the country and province. To gauge the extent to which the instrument takes care of such time-invariant country-province endogeneity, I estimate a panel specification, specifically

$$Y_{o,d,t} = \alpha_{o,t} + \alpha_{d,t} + \delta \ln(Dist_{o,d}) + \beta M_{o,d,t} + \varepsilon_{o,d,t} \tag{6}$$

$$Y_{o,d,t} = \alpha_{o,t} + \alpha_{d,t} + \alpha_{o,d} + \beta M_{o,d,t} + \varepsilon_{o,d,t} \tag{7}$$

where $Y_{o,d,t} \in \{\mathbf{1}[C_{o,d,t} > 0], \ln(C_{o,d,t} + 1)\}$ for the value of drugs confiscated in d from o in year t $C_{o,d,t}$ for both imports and intended re-exports. $M_{o,d,t}$ is measured as the log of the bilateral immigrant population in thousands plus 1, where the bilateral immigrant population is derived from annual tabulations taken from Spain's local population registries at the country-by-province level. I estimate equations 6 and 7 for the years 2002 through 2016.

I modify the instrumental variables for the panel analysis by including the cross-sectional 1991–2001 push-pull instrument

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

as well as a time-varying instrument that predicts bilateral immigrant inflows between 2001 and year t,

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

I compute immigrant inflows between 2001 and t as the net change in the bilateral immigrant population as measured in the population registry. To improve the first-stage fit (and similar to Burchardi et al., 2019), I also add squared versions of the instrumental variables.[31]

For imports, I estimate equation 6 in Table A.5 and equation 7 in Table A.6. For re-exports, I estimate equation 6 in Table A.7 and equation 7 in Table A.8. The estimated coefficients are in line with my baseline estimates in Tables 2 and 3, suggesting that time-invariant country-province level confounders are not significantly shaping my baseline results.

3.8.5 Legal Trade

To gauge the magnitude of the effect size estimated in Section 3.5 for illegal trade relative to legal trade, I estimate the relationship between the bilateral immigrant population and legal trade. To measure legal trade volume, I turn to the ADUANAS-AEAT dataset provided by the Spanish government. This dataset provides transaction-level data and includes informa-

[31] Without the squared terms, I obtain a first-stage F-statistic of approximately 14. My second stage results also carry through without the squared terms for the instrumental variables.

tion 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.

Because I find some sensitivity of this relationship with respect to functional form choices, I estimate the generalized method of moments with moments

$$E\left[(\ln(X_{o,d}^{legal}+1)-\delta_2-\beta_2\ln(1+\pi_2 migrants_{o,d}^{2011}))\times Z_{o,d}\right]=0$$

where $X_{o,d}$ is the value of legal goods imported into province d originating from country o and for instrument set

$Z_{o,d}=\left(I_{o,d}^{IV,1991-2001},I_{o,d}^{IV,2001-2011},(I_{o,d}^{IV,1991-2001})^2,(I_{o,d}^{IV,2001-2011})^2,(I_{o,d}^{IV,1991-2001}\times I_{o,d}^{IV,2001-2011})\right)'$.[32]

Column 2 of Table 4 shows the results. I estimate that a 10% rise in the number of immigrants increases legal trade by about 13%, a magnitude comparable to the effect of immigrants on illegal drug confiscations.[33]

4 General Equilibrium Responses and Enforcement Intensity

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 two exercises 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.

[32] With nearly every province-origin country pair having positive trade I do not have enough variation along the extensive margin of trade to also estimate the comparable moment for legal trade.

[33] As shown in column 2 of Table 4, I estimate that $\hat{\beta}=1.36$, $SE=0.1$ and $\hat{\pi}=0.013$, $SE=0.0068$. To get the elasticity from this nonlinear equation, I compute that $\frac{X_{o,d}^{2011}[M_{o,d}^{2011}=1.1\times 963]}{X_{o,d}^{2011}[M_{o,d}^{2011}=963]}-1=\exp\left(1.36\left(\ln\left(1+0.012\times(1.1\times 963)\right)-\ln\left(1+0.012\times 963\right)\right)\right)-1=0.127$.

4.1.1 Quantitative Exercise

First, I consider the plausibility of variation of enforcement intensity explaining the quantitative magnitudes that I estimated in Section 3.2. In particular, I ask how much bilateral enforcement intensity would have to increase to fully explain the observed effect of immigrants on drug confiscations.

To formalize this notion, take the derivative of equation 1 with respect to the number of immigrants:

$$\frac{dC_{o,d}}{dM_{o,d}} = E_{o,d}\frac{\partial X_{o,d}}{\partial M_{o,d}} + X_{o,d}\frac{\partial E_{o,d}}{\partial M_{o,d}} \tag{10}$$

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

$$\epsilon_{C,M} = \epsilon_{X,M} + \epsilon_{E,M} \tag{11}$$

where $\epsilon_{a,b}$ is the elasticity of a with respect to b. In Section 3.2, I estimate $\hat{\epsilon}_{C,M} = 1.2$. Suppose now that actual drug flows are not at all affected by the bilateral immigrant population, that is, $\epsilon_{X,M} = 0$. To assess the plausibility of this assumption, I first calculate a back-of-the-envelope estimate of the elasticity of enforcement intensity to immigrant population, $\hat{\epsilon}_{E,M}$.

I consider the effects of a 2 standard deviation increase in the predicted bilateral immigrant population, residualized on origin and destination fixed effects and log distance. The median of predicted immigrants is 11, and a 2 standard deviation increase raises this to 332.[34] This represents an increase in the country-province-specific immigrant population of 3000%, which would require a 3600% increase in enforcement intensity if my results were driven entirely by changes in enforcement.

To gauge the size of the implied increase in enforcement intensity, I compute a rough estimate of the fraction of drugs confiscated by Spain. I calculate this as

$$\hat{E}_{Spain} = \frac{C_{Spain}}{Y_{EU} \times \frac{C_{Spain}}{C_{EU}} + C_{Spain}}$$

where Y_{EU} is the size of the market for illegal drugs in the European Union and C_X is the value of drugs confiscated by X. I focus on the market for cannabis and cocaine, as they are the primary drugs appearing in the Spanish confiscations data.

[34] Where $11 \approx (exp(0.11) - 1) \times 1000$ and the standard deviation of residualized bilateral immigrant population is ≈ 0.14.

For Y_{EU}, I use the European Monitoring Centre for Drugs and Drug Addiction[35] estimate for the size of the market for cocaine and cannabis in the European Union of about 20 billion USD in 2013. I compute $\frac{C_{Spain}}{C_{EU}}$ using the international UNODC confiscations data and find that Spain confiscated 78% of cannabis and cocaine by value. Between 2011 and 2016, on average, 1 billion USD worth of cocaine and cannabis was confiscated by Spain. I therefore compute that about 6% of cocaine and cannabis entering Spain are confiscated by Spanish law enforcement. Therefore an increase in enforcement intensity of 3600% would raise enforcement intensity to 2.17, which is infeasible since $E_{o,d} \leq 1$.

4.1.2 Extensive Margin of Trafficking

Next, 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.

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, $\frac{\partial X_{o,d}}{\partial M_{o,d}}$. 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

$$\mathbf{1}\{C_{o,d} > 0\} = \alpha_o + \alpha_d + \beta M_{o,d} + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d} \tag{12}$$

for the subset of observations for which I predict that $X_{o,d} \approx 0$.[36]

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

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

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

[35]https://www.emcdda.europa.eu/system/files/publications/3096/Estimating%20the%20size%20of%20main%20drug%20markets.pdf

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

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 \$1,000 worth of drugs confiscated. While the point estimate falls when subsetting to the sample predicted to be on the extensive margin, the two estimates in columns 1 and 2 are statistically indistinguishable, suggesting enforcement variation cannot fully explain my bilateral results.

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, immigrants from one country may adjust 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 and Use

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

$$\ln Y_{d,t} = \alpha_d + \alpha_t + \beta \ln M_{d,t} + \epsilon_{d,t} \tag{14}$$

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):

$$IV_{d,t} = \ln \left[\sum_o \left(\frac{Immigrants_{o,d,1981}}{Immigrants_{o,1981}} \right) \times Immigrants_{o,t} \right] \tag{15}$$

where $Immigrants_{o,t}$ refers to the number of immigrants from o living in Spain in year t.[37]

Because I am exploiting less variation than in my baseline gravity estimation, interpreting

[37] I 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 A.9.

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 autonomous communities that shape the distribution of immigrant populations in 1981, the distribution of immigrant populations in in the 2000s, and the distribution of drug trafficking across space in the 2000s.

In Figure A.25 I show the first-stage fit. The instrument well predicts the immigrant population across Spanish provinces over time.

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 19% 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 $DrugUsers_{d,t}^{Native}$, the number of native-born drug users per capita measured using the 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.

4.2.2 Drug Arrests and Cultivation

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

$$\ln Y_d = \alpha + \beta \ln M_{d,2011} + \gamma \ln Population_{d,1981} + \epsilon_{d,t} \tag{16}$$

for some measure Y_d of illegal drug activity in d and the log number of immigrants from all origins $M_{d,2011}$ in 2011. I again use the shift-share instrumental variable defined in equation 15.

I first estimate 16, measuring illegal drug activity Y_d as the number of native-born Spaniards arrested for drug trafficking offenses in province d between 2011 and 2016. I find that a larger immigrant population does not lead to statistically significant differences in drug trafficking arrest rates of the native-born, as shown in column 2 of Table 7.

Finally, I measure illegal drug activity as the log number of cannabis plants confiscated.

Spain produces a small but non-trivial amount of cannabis.[38] 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.[39] I find that as the local immigrant population increases, there is no effect on the number of cannabis plants confiscated locally, suggesting there is not a large domestic production response to changes in 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 or a path to citizenship. A lack of legal status may hinder their access to the formal labor market, which lowers the opportunity cost of crime (Becker, 1968; Ehrlich, 1973). This may result in an increase in criminal activity among immigrants, as found empirically by Mastrobuoni and Pinotti (2015), Pinotti (2017), and Freedman et al. (2018). Hence a lack of legal status may lead immigrants to illegally traffic drugs.

To assess whether this intuition holds for drug trafficking, I conduct two exercises. First, I use a gravity equation to estimate separately the effect of irregular immigrants (those without legal status) and regular immigrants on drug confiscations and find that my bilateral results are driven entirely by irregular immigrants. Second, I exploit an extraordinary regularization program in 2005 to explore the long-run dynamics of receiving legal status and later obtaining citizenship, and I find that granting immigrants citizenship can significantly reduce drug trafficking.

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

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

[38]Alvarez 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.

[39]I 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.

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 irregular migration is an important factor in explaining the connection I find between immigrants and drug trafficking, I modify my baseline specification, equation 2, to include two separate terms for the bilateral immigrant population by regular ($M_{o,d}^{reg}$) and irregular ($M_{o,d}^{irreg}$) status:

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

where, as in the baseline, $Y_{o,d}$ is either a dummy for whether any confiscation occurred or the log value of drugs confiscated plus one. 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 4 may not address. In particular, there may be some characteristic of immigrants, such as a taste for risk-taking, which drives selection into both irregularity and 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.

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 with the lagged leave-out fraction of immigrants with legal status L,

$$IV_{o,d}^{D,L} = m_{o,d}^{L} \times IV_{o,d}^{D} \tag{19}$$

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 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—either persistent from 2003 to 2011 or present in both province d and another province outside d's autonomous community—at the province-country-pair level driving selection of immigrants into both irregular status and drug trafficking.

More concretely, consider the case of Moroccan immigrants living in Barcelona. $m^L_{o,d}$ 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, for example, 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—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).

In Panel A of Table 8 I show the results for estimating equation 18; in Panel B I show results when using the instruments defined in equation 19. I find that a 10% increase in the bilateral *irregular* immigrant population raises the likelihood of an illegal drug confiscation by 1.9 percentage points (column 2 of panel B). By contrast, a 10% increase in the bilateral *regular* immigrant population slightly reduces illegal drug confiscations and the estimated coefficient is statistically insignificant.[40] A 10% increase in the bilateral population of irregular immigrants raises the value of drugs confiscated by 29%, while 10% increase in the bilateral regular immigrant population leads to a small and statistically insignificant increase in the value of drugs confiscated (column 4 of panel B).[41] Effect sizes may be larger in the 2SLS (panel B) than in the OLS (panel A) due to greater measurement error in the population of immigrants by legal status, since I estimate these populations as outlined in Section 5.1.

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

[40]Using $\hat{\beta}^{Reg} = -0.112$ from column 2 and mean value of bilateral immigrant population of 933, I find that $\mathbb{1}\left[C^{2011-2016}_{o,d} > 0 | M^{2011}_{o,d} = 933\right] = -0.112\left(\ln\left(1+\frac{933\times1.1}{1000}\right) - \ln\left(1+\frac{933}{1000}\right)\right) \approx 0.005$ and for $\hat{\beta}^{Irreg} = 0.403$, this is 0.019.

[41]Using $\hat{\beta}^{Reg} = 0.0383$ from column 4, we have: $\frac{C^{2011-2016}_{od}[M^{2011}_{o,d}=1.1\times933]}{C^{2011-2016}_{od}[M^{2011}_{o,d}=933]} - 1 = \exp\left(0.0383\left(\ln\left(1+\frac{1.1\times933}{1000}\right) - \ln\left(1+\frac{933}{1000}\right)\right)\right) - 1 \approx 0.0018$. For irregular migration, this is 0.29.

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).

To better understand the effects of the regularization, I estimate an event study at the province-by-year level. This differs from my baseline cross-section estimates in Section 3.2 in that I use year-to-year variation in drug confiscations. At the bilateral level, confiscations can occur highly irregularly, with no confiscations for several years followed by a year with one massive confiscation. This 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 province level. Doing this has the added benefit of improving measurement of the number of irregular immigrants, as the bilateral-level measurement excludes many countries and appears to censor bilateral links with very few immigrants.

I estimate this event study using the equation

$$Y_{d,t} = \sum_{t \neq 2004} \theta_t \times m_d^{2003,irregular} + \delta_d + \delta_t + \epsilon_{d,t} \tag{20}$$

where $m_d^{2003,irregular}$ is the number of irregular immigrants in 2003 imputed as in equation 17. I plot the θ_t coefficients in Figure 5, both for whether any confiscation occurred, $Y_{d,t} = \mathbf{1}\{C_{d,t} > 0\}$, and the log value of drug confiscations, $Y_{d,t} = \ln(C_{d,t} + 1)$.

I find that the 2005 regularization led to a sudden jump in the number of work authorizations granted to immigrants in Spain, as shown in Figure A.26. In addition, naturalizations of immigrants increased markedly in 2005, 2010, and 2013. The 2005 increase may be related to the 2000 regularization of several hundred thousand immigrants, while the 2010 increase relates to the 2005 regularization under study here. The 2013 spike in citizenship granting is due to solving technical and bureaucratic issues that had delayed issuance of citizenship for many immigrants.[42]

In Figure 5 I show the effect of the 2005 regularization on total drug confiscations, which declined significantly in 2010 and stayed low thereafter. Moreover, this decline came primarily from declines in cocaine confiscations, as shown in Figure 6. The decline in cocaine

[42] This is based on a conversation with an employee at Spain's National Statistics Institute.

confiscations is consistent with the increase in naturalizations for Latin Americans but a modest decrease in naturalizations for immigrants from Africa, as shown in Figure 7.

Overall, these results suggest that granting legal status to immigrants plays an important role in reducing drug trafficking by putting them on a path to citizenship. Taking the average of the coefficients from 2010 to 2016 for the event study estimated on the extensive margin of trafficking suggests that a province granting legal status and subsequent citizenship to an additional 10,000 immigrants reduces the likelihood of a confiscation occurring in that province by 2.3%.

These results differ somewhat from the literature on immigrant legal status on crime. Freedman et al. (2018), Mastrobuoni and Pinotti (2015), and Pinotti (2017) find an immediate drop in immigrant criminal activity as a result of legalization, whereas I find a delayed effect. Pinotti (2017) provides a useful comparison. He shows that for immigrants with weak ties to the formal labor market, legalizations' impact on crime is substantial, but he finds no effect for those with the strongest ties to the formal labor market he finds no effect. Similarly, the 2005 regularization that I study only grants legal status to immigrants with a labor contract already lined up, often a labor relationship that pre-existed 2005 but is simply being formalized by the program. My results are therefore in line with Pinotti (2017) in terms of the immediate effects of legalization, but I look at an extended time horizon and find a reduction in crime around the time immigrants become eligible for citizenship. Therefore the results I present here may be a lower bound on the effects of immigrant legalization on crime.

To get a sense of how the regularization would have affected drug trafficking if it were not conditioned on immigrants' formal labor sector ties, I do a back-of-the-envelope calculation using the instrumented gravity estimates from Section 5.2. Using the data and method described in Section 5.1, I estimate that in 2004 about a third of all immigrants in Spain were irregular. In addition, using the coefficient on irregular immigrants from column 4 of Table 8, I estimate that the regularization program reduced illegal drug trafficking by about 20%.[43] Note, however, that this back-of-the-envelope calculation abstracts away from any offsetting general equilibrium effects.

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

[43] $\exp(5.459 \times (\log(1 + 134 \times \frac{2}{3}/1000) - \log(1 + 134/1000)) - 1 \approx 0.197$.

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 Confiscations (OLS)

	(1)	(2)	(3)	(4)
	Outcome: Confiscations of Imported Drugs 2011-2016 (Dummy)			
Log Immigrants 2011	0.220***	0.187***	0.205***	0.137***
	(0.00766)	(0.0150)	(0.00991)	(0.0130)
Observations	5564	5564	5564	5564
	Confiscations of Drugs Intended for Re-Export (Dummy)			
Log Immigrants 2011	0.0899***	0.114***	0.0613***	0.0609***
	(0.0135)	(0.0228)	(0.00756)	(0.0146)
Observations	5564	5564	5564	5564
	Confiscations of Imported Drugs 2011-2016 (Log Value)			
Log Immigrants 2011	3.006***	2.628***	2.800***	1.965***
	(0.157)	(0.298)	(0.148)	(0.243)
Observations	5564	5564	5564	5564
	Confiscations of Drugs Intended for Re-Export 2011-2016 (Log Value)			
Log Immigrants 2011	1.074***	1.393***	0.722***	0.751***
	(0.186)	(0.302)	(0.102)	(0.186)
Observations	5564	5564	5564	5564
Country FE	No	Yes	No	Yes
Province FE	No	No	Yes	Yes
Log dist	Yes	Yes	Yes	Yes

Notes: The table presents OLS estimates of equation 2 at the country-province level. Standard errors are clustered by 52 provinces in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Effect of Immigrants on Drug Import Confiscations

	(1) First-stage: Log Immigrants 2011	Drug Confiscations 2011-2016 (2) 2SLS: (dummy)	Drug Confiscations 2011-2016 (3) 2SLS: (ln value)
Predicted immigration, 2001-2011	0.0374**		
	(0.0140)		
Predicted immigration, 1991-2001	0.154***		
	(0.0261)		
Log Immigrants 2011		0.105***	2.322***
		(0.0381)	(0.549)
Observations	5564	5564	5564
R^2	0.699	0.045	0.061
Origin FE	Y	Y	Y
Dest. FE	Y	Y	Y
Ln dist.	Y	Y	Y
1st-stg F-stat.	23.4	23.4	23.4

Notes: The table presents coefficient estimates from IV regressions of equation 2 at the country-province level. I instrument for *Log Immigrants 2011* using $\{IV^D_{o,d} = I^D_{o,-a(d)} \times I^D_{-c(o),d}/I^D_{-c(o)}\}_{1991-2001,2001-2011}$ as the excluded instruments, with the first-stage shown in column 1. The dependent variable is a dummy for whether any drugs from country o were confiscated in province d between 2011 and 2016 in column 2 and the log value (in 2012 USD) of drugs from country o confiscated in province d between 2011 and 2016 plus 1. All regressions control for log distance. Standard errors are clustered at the province level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effect of Immigrants on Drug Re-Export Confiscations

	(1) First-stage: Log Immigrants 2011	Drug Confiscations 2011-2016 (2) 2SLS: (dummy)	(3) 2SLS: (ln value)
Predicted immigration, 2001-2011	0.0374^{**}		
	(0.0140)		
Predicted immigration, 1991-2001	0.154^{***}		
	(0.0261)		
Log Immigrants 2011		0.0802^{***}	1.277^{***}
		(0.0211)	(0.337)
Observations	5564	5564	5564
R^2	0.699	0.013	0.008
Origin FE	Y	Y	Y
Dest. FE	Y	Y	Y
Ln dist.	Y	Y	Y
1st-stg F-stat.	23.4	23.4	23.4

Notes: The table presents coefficient estimates from IV regressions of equation 2 at the country-province level. I instrument for *Log Immigrants 2011* using $\{IV^D_{o,d} = I^D_{o,-a(d)} \times I^D_{-c(o),d}/I^D_{-c(o)}\}_{1991-2001,2001-2011}$ as the excluded instruments, with the first-stage shown in column 1. The dependent variable is a dummy for whether any drugs intended for re-export to country o were confiscated in province d between 2011 and 2016 in column 2 and the log value (in 2012 USD) of drugs intended for re-export to country o confiscated in province d between 2011 and 2016 plus 1. All regressions control for log distance. Standard errors are clustered at the province level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Effect of Immigrants on Drug Import Confiscations and Legal Imports (GMM)

	(1) Drug Smuggling	(2) Legal Trade
β_1		
	0.137***	
	(0.021)	
π_1		
	0.006**	
	(0.006)	
β_2		
	2.52***	1.365***
	(0.39)	(0.0998)
π_2		
	0.003**	0.0127*
	(0.003)	(0.00679)
Observations	5564	5136

Standard errors clustered by 52 provinces in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample size in column 2 falls relative to column 1 due to miscoding of certain provinces (specifically Ceuta, Melilla, and the Canary Islands) in the AEAT data on legal trade. I do not estimate β_1 and π_1 for legal trade because virtually all bilateral links engage in some trade.

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

	Drug Confiscations 2011-2016 (Dummy)	
	(1)	(2)
Log Immigrants 2011	0.105***	0.0541**
	(0.0381)	(0.0255)
Observations	5564	4015
R^2	0.045	0.017
Origin FE	Y	Y
Dest. FE	Y	Y
Ln dist	Y	Y
1st-stg F-stat.	23.4	20.0
Sample	All	< 1000 USD seized

Notes: The table presents coefficient estimates from IV regressions of equation (15) at the country-province level. *Log immigrants 2011* is instrumented with the leave-out push-pull IV from equation (3). In column 2, I subset to the set of country-province pairs for which predicted confiscations (using equation 16) fall below \$1,000. Standard errors are clustered by 52 provinces 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) First-Stage: Log immigrants	(2) 2SLS: Log value confiscated	(3) 2SLS: Log native-born used drugs last 12 mo.	(4) 2SLS: Log native-born ever used drugs
Shift-Share IV	0.180***			
	(0.0415)			
Log Immigrant population		19.32*	2.042	4.572
		(11.21)	(2.194)	(3.282)
Observations	728	728	310	312
Kleibergen-Paap F-stat	18.9	18.9	4.3	4.2
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates from IV regressions of equation (10) at the province-year level. I instrument for *Log Immigrants* using the excluded instrument defined in equation (11), with the first-stage shown in column 1. In column 2, the dependent variable is the log of 1 plus the value of illegal drugs confiscated as measured in the UNODC Individual Seizures Data. 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). 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 Illegal Drug Activity (Province Cross-Section)

	(1) First-stage: Log Immigrants 2011	(2) 2SLS: Log native-born drug traf arrests	(3) 2SLS: Log cannabis plants seized
Ethnic Enclave IV	0.150**		
	(0.0637)		
Log Immigrants 2011		1.829	0.761
		(1.326)	(0.633)
Observations	52	52	50
R^2	0.621	.	0.571
1st-stg. F-stat	5.6	5.6	5.6
Dep. var. mean (unlogged)	1.0e+05	7.0e-05	4003

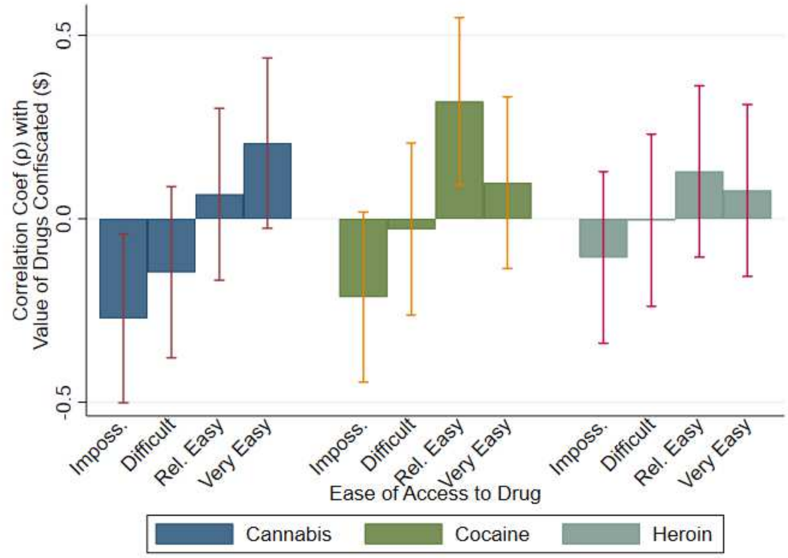
Notes: The table presents coefficient estimates from IV regressions of equation 16 at the province level. I instrument for *Log Immigrants 2011* using the excluded instrument defined in equation 15, with the first-stage shown in column 1. In column 2, the dependent variable is the log of the number of individuals with Spanish nationality arrested for drug trafficking offenses. The dependent variable of columns 3 is the log number of cannabis plants confiscated by Spanish law enforcement in 2013. 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

	OLS: Confiscations of Imported Drugs 2011-2016			
	(1)	(2)	(3)	(4)
	(dummy)	(dummy)	(log value)	(log value)
Log Immigrants 2011	0.164***		2.791***	
	(0.0148)		(0.229)	
Log Regular Immigrants 2011		0.0346		0.592
		(0.0267)		(0.411)
Log Irregular Immigrants 2011		0.220***		3.849***
		(0.0249)		(0.428)
Observations	3116	3116	3116	3116
	2SLS: Confiscations of Imported Drugs 2011-2016			
	(dummy)	(dummy)	(log value)	(log value)
Log Immigrants 2011	0.155***		3.467***	
	(0.0364)		(0.477)	
Log Regular Immigrants 2011		-0.112		0.0383
		(0.0856)		(1.266)
Log Irregular Immigrants 2011		0.403***		5.459***
		(0.0821)		(1.121)
Observations	3116	3116	3116	3116
Kleibergen-Paap 1st-stg. F-stat.	61.0		61.0	
SW 1st-stg. F-stat. (regular immigrants)		43.2		43.2
SW 1st-stg. F-stat. (irregular immigrants)		69.9		69.9

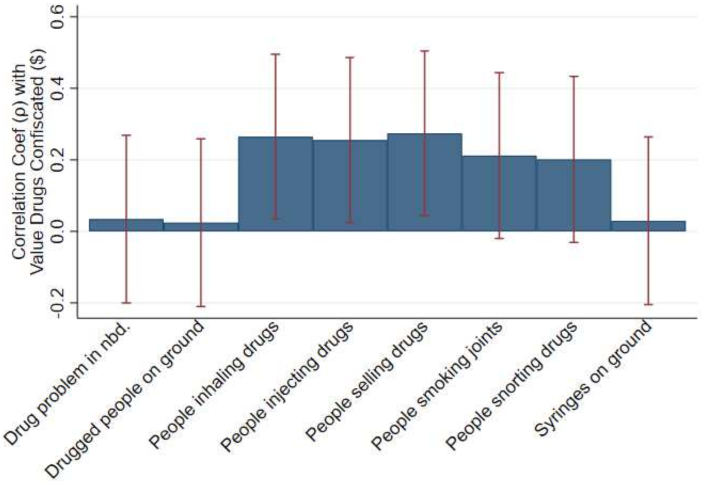
Notes: The table presents estimates of equation 18 at the country-province level. Standard errors are clustered by 52 provinces in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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



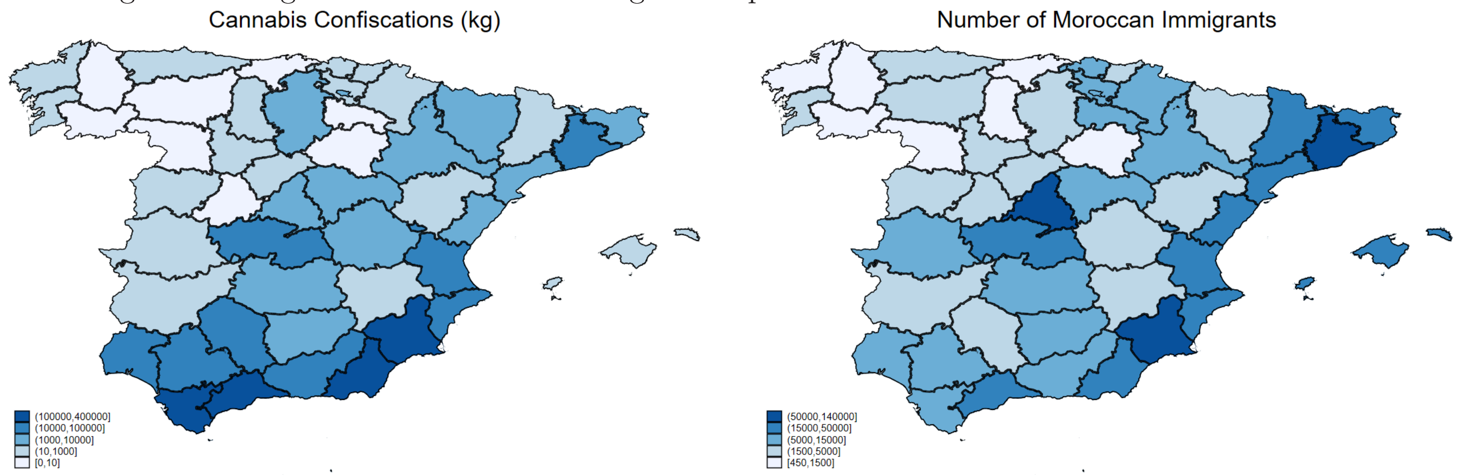
Notes: This figure shows Pearson correlation coefficients between the amount of confiscations per capita of a particular drug with the fraction of respondents in a province who report finding it impossible/difficult/relatively easy/very easy to obtain that drug within 24 hours averaged over the 2011, 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 Drug Availability (across all drugs)



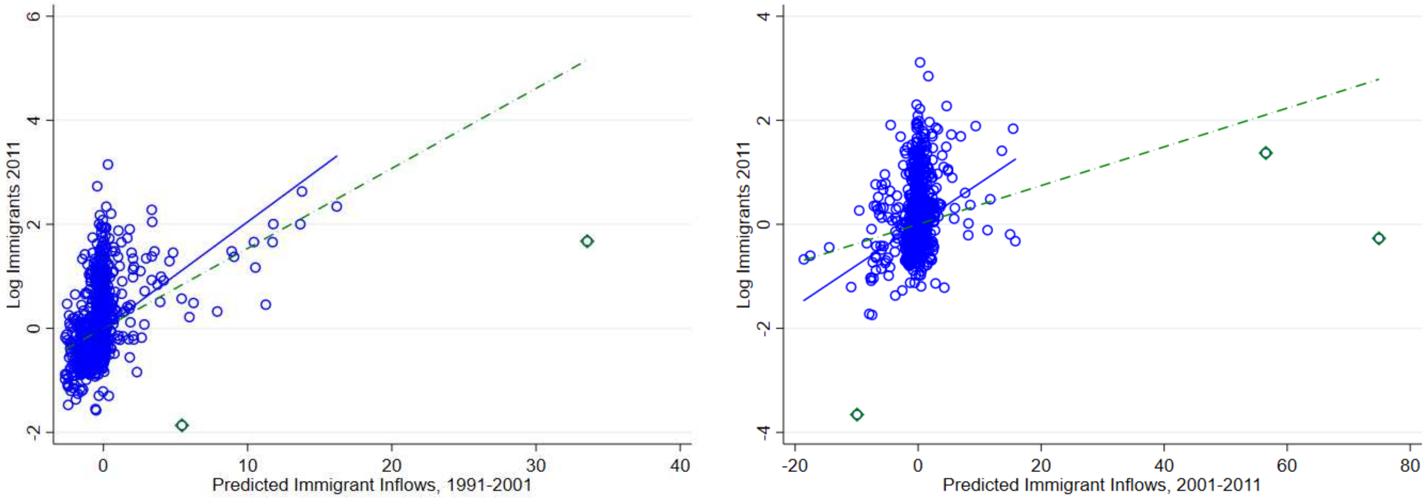
Notes: This figure plots Pearson correlation coefficients between illegal drug confiscations (measured in dollars) per capita across all drugs (as appropriate) with the fraction of respondents in the province who reported observing the listed drug-related behaviors either "frequently" or "very frequently" or, for the first bar, "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?". As appropriate, I drop cannabis from the drug confiscation variable in the correlation specifically for the questions on people snorting or injecting drugs or syringes being on the ground. Ninety confidence intervals are shown in red. Correlations estimated on a cross-section of 52 Spanish provinces.

Figure 3: Drug Confiscations and Immigrant Population: The Case of Morocco and Cannabis



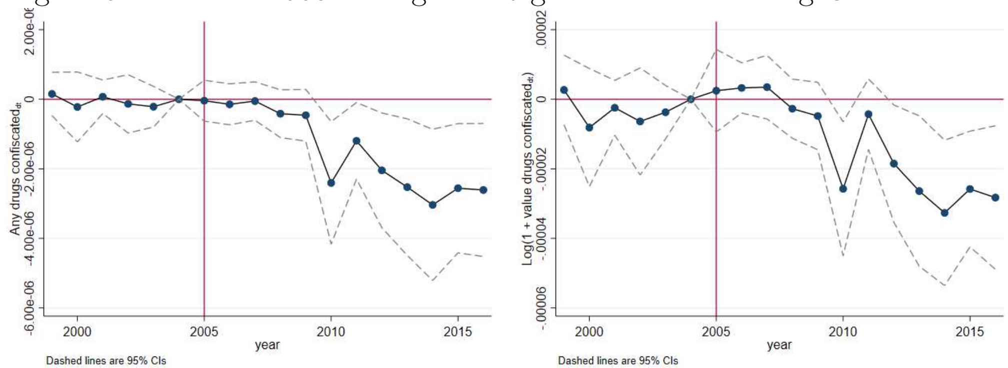
Notes: The figure on the left shows the distribution across Spanish provinces of cannabis confiscations between 2011 and 2016 originating from Morocco; the figure on the right shows the distribution across Spanish provinces of the number of individuals with Moroccan nationality in 2011.

Figure 4: First-Stage Fit



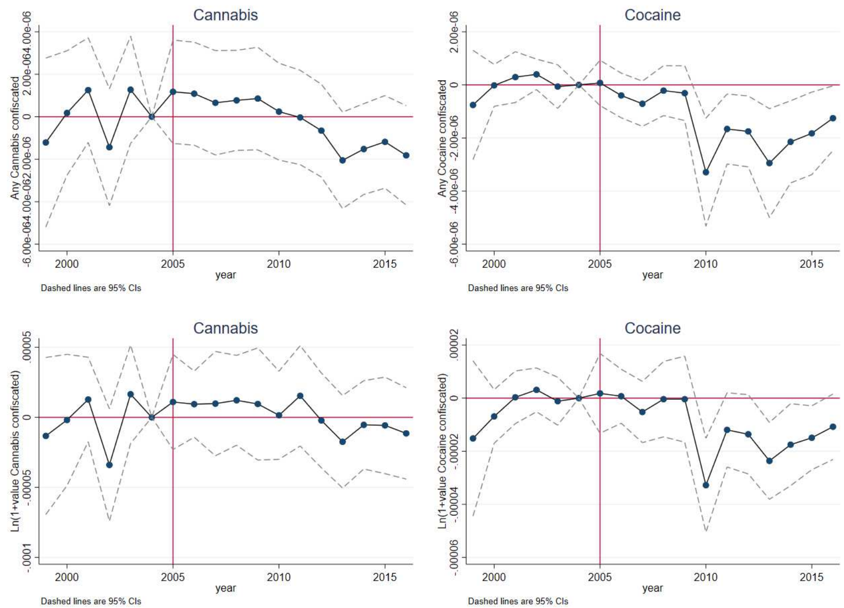
Notes: The figure shows the conditional scatter plots of *Log Migrants* 2011 with the instruments for immigrant inflows for decades 1991 to 2001 (on the left) and 2001 to 2011 (on the right). Both *Log Migrants* 2011 and the predicted inflows are residualized on origin and destination fixed effects, 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 Confiscations



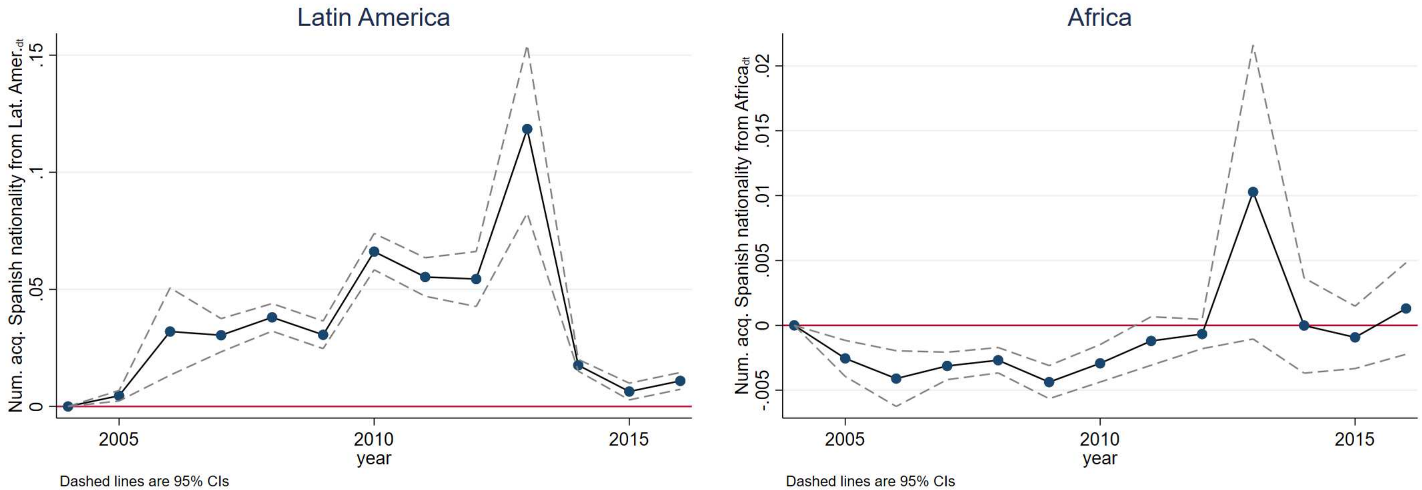
Notes: The figure shows event study plots of the effect of the 2005 immigrant regularization on whether any drugs were confiscated locally (chart on the left) and the log of one plus the value of drugs confiscated locally (chart on the right). Plots are estimated using equation 20.

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 (figures on the left) and cocaine (figures on the right). The dependent variable for the top figures are whether any of the drugs were confiscated locally in that year, and on the bottom the log of one plus the value of the drug confiscated locally. Plots are estimated using equation 20.

Figure 7: Effect of 2005 Immigrant Regularization on Naturalizations by Continent of Origin



Notes: The figure shows event study plots of the effect of the 2005 immigrant regularization on the number of citizenship acquisitions of immigrants from Latin America (figure on the left) and from Africa (figure on the right). Plots are estimated using equation 20.

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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

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

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

$$F_d(z) = e^{-T_d z^{-\theta}} \tag{A.2}$$

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 $M_{o,d}$,

$$\ln \tau_{o,d} = \alpha_0 \ln t_{o,d} - \alpha_1 \ln M_{o,d} \tag{A.3}$$

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

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

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

$$\ln X_{o,d} = \delta_o + \delta_d + f(gravity_{o,d}) + \beta_2 \ln M_{o,d} + \varepsilon_{o,d} \tag{A.4}$$

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 (A.4) 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

$$C_d = \frac{1}{\gamma}\left(\frac{T_d}{\pi_{d,d}}\right)^{\frac{1}{\theta}} \tag{A.5}$$

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

$$\pi_{dd} = \frac{T_d(w_d)^{-\theta}}{\sum_o T_o(w_o\tau_{o,d})^{-\theta}} \tag{A.6}$$

Combining the equations A.5 and A.6,

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

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

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

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

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

Starting from the previous expression, substituting in equation A.3 for $d \ln \tau_{o,d}$ to obtain

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

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

$$\ln C_d - B_0 = (1 - \pi_{dd})(\ln w_d + B_1) + \frac{\pi_{d,d}}{\theta}(\ln T_d + B_2) + \alpha_1 \sum_{o \neq d} \pi_{o,d}(\ln M_{o,d} + B_o) + \int \varepsilon_d$$

$$\ln C_d = (1 - \pi_{d,d}) \ln w_d + \frac{\pi_{d,d}}{\theta} \ln T_d + \alpha_1 \sum_{o \neq d} \pi_{o,d} \ln M_{o,d} + (\frac{B_2}{\theta} - B_1)\pi_{d,d} + \alpha_1 \sum_{o \neq d} B_o \pi_{o,d} + \epsilon_{od}$$

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 A.5 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.

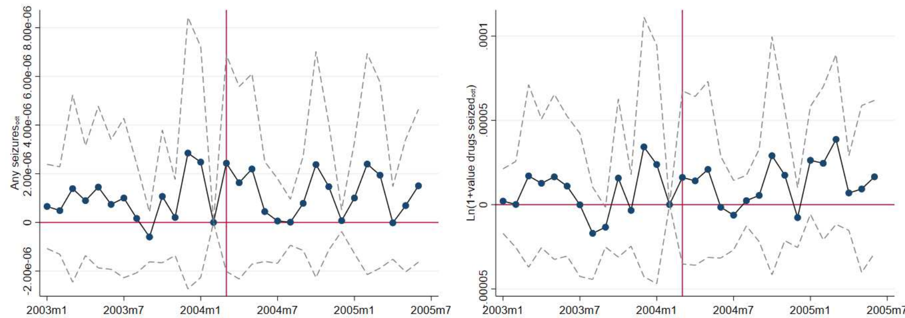
To assess whether this change in enforcement intensity caused a notable increase in drug confiscations, I estimate

$$Y_{o,d,t} = \alpha_{o,d} + \alpha_t + \sum_{t \neq Mar.\ 2004} \theta_t \times M^{2003}_{Morocco,d} + \epsilon_{o,d,t}$$

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 A.8 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 A.8: 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 A.1: Robustness to Different Functional Forms, Any Confiscation

	Drug Confiscations 2011-2016 (Imports, Dummy)		
	(1)	(2)	(3)
$M_{o,d}^{2011}$	0.00000431*		
	(0.00000250)		
$\ln\left(\frac{M_{o,d}^{2011}}{1000}\right)$ (-1 for ∞)		0.0884***	
		(0.0250)	
$\left(M_{o,d}^{2011}\right)^{1/3}$			0.0140**
			(0.00590)
Observations	5564	5564	5564
Country FE	Y	Y	Y
Province FE	Y	Y	Y
Ln dist	Y	Y	Y
1st-stg F-stat.	311.7	7.3	50.5

Standard errors clustered by 52 provinces in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Robustness to Different Functional Forms, Log Value of Confiscation

	Drug Confiscations 2011-2016 (Imports, Dummy)		
	(1)	(2)	(3)
$M_{o,d}^{2011}$	0.0000978**		
	(0.0000423)		
$\ln\left(\frac{M_{o,d}^{2011}}{1000}\right)$ (-1 for ∞)		1.960***	
		(0.350)	
$\left(M_{o,d}^{2011}\right)^{1/3}$			0.312***
			(0.0904)
Observations	5564	5564	5564
Country FE	Y	Y	Y
Province FE	Y	Y	Y
Ln dist	Y	Y	Y
1st-stg F-stat.	311.7	7.3	50.5

Standard errors clustered by 52 provinces in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Effect of Bilateral Immigrant Population by Origin Drug-Hubness

	Drug Confiscations 2011-2016			
	(1)	(2)	(3)	(4)
	Dummy	Log Value	Dummy	Log Value
Log Immigrants 2011	0.112***	2.226***	0.146***	4.706***
	(0.0372)	(0.530)	(0.0429)	(0.664)
Log Immigrants 2011 × % of seized drugs from o	0.0206	3.128		
	(0.237)	(3.646)		
Log Immigrants 2011 × Drug hubness rank			-0.00141**	-0.0763***
			(0.000695)	(0.0117)
Observations	5564	5564	5564	4836
R^2	0.046	0.065	0.059	0.092
Origin FE	Y	Y	Y	Y
Dest. FE	Y	Y	Y	Y
Ln dist	Y	Y	Y	Y
1st-stg F-stat.	23.8	23.8	12.8	14.0

Notes: The table presents coefficient estimates from IV regressions of equation 2, modified to include a term interacting the log immigrant population with a measure of the immigrants' origin country drug-hubness at the country-province level. I instrument for *Log Immigrants 2011* using the IV defined in equation 4 and the IV interacted with the measure of drug hubness. 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 the log of 1 plus the value (in 2012 USD) of illegal drugs imported from country o were confiscated in province d between 2011 and 2016 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 province level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Gravity Specification: Alternative Standard Errors

	(1) First-stage: Log Immigrants 2011	Drug Confiscations, 2011-2016 (2) 2SLS: dummy imports	(3) 2SLS: log value imports	(4) 2SLS: dummy re-export	(5) 2SLS: log value re-export
PANEL A: HETEROSKEDASTICITY-ROBUST					
Predicted immigration, 2001-2011	0.0374*				
	(0.0171)				
Predicted immigration, 1991-2001	0.154***				
	(0.0328)				
Log Immigrants 2011		0.105**	2.322***	0.0802*	1.277*
		(0.0359)	(0.534)	(0.0386)	(0.540)
Constant	0.127				
	(0.293)				
Kleibergen-Paap F-stat.	8.5	12.3	12.3	12.3	12.3
PANEL B: CLUSTERED BY COUNTRY					
Predicted immigration, 2001-2011	0.0374				
	(0.0205)				
Predicted immigration, 1991-2001	0.154***				
	(0.0331)				
Log Immigrants 2011		0.105	2.322*	0.0802	1.277*
		(0.0646)	(0.948)	(0.0419)	(0.638)
Constant	0.127				
	(0.194)				
Kleibergen-Paap F-stat.	9.9	11.5	11.5	11.5	11.5
PANEL C: CLUSTERED BY PROVINCE (BASELINE)					
Predicted immigration, 2001-2011	0.0374*				
	(0.0140)				
Predicted immigration, 1991-2001	0.154***				
	(0.0261)				
Log Immigrants 2011		0.105**	2.322***	0.0802***	1.277***
		(0.0381)	(0.549)	(0.0211)	(0.337)
Constant	0.127				
	(0.413)				
Kleibergen-Paap F-stat.	16.6	23.4	23.4	23.4	23.4
PANEL D: CLUSTERED TWO-WAYS BY COUNTRY AND PROVINCE					
Predicted immigration, 2001-2011	0.0374*				
	(0.0179)				
Predicted immigration, 1991-2001	0.154***				
	(0.0264)				
Log Immigrants 2011		0.105	2.322*	0.0802**	1.277*
		(0.0658)	(0.955)	(0.0267)	(0.479)
Constant	0.127				
	(0.346)				
Kleibergen-Paap F-stat.	15.9	19.8	19.8	19.8	19.8

Notes: The table presents regression results at the country-province level for the first-stage (column 1) and the second stage (columns 2–5) of the baseline gravity specification. All regressions control for province and nationality fixed effects and log distance. In Panel A, I compute heteroskedasticity-robust standard errors with no clustering. In Panel B, I cluster by nationality; in Panel C by province, as in the baseline specification; and in Panel D, I cluster two-ways by country and province. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.5: Effect of Immigrants on Import Confiscations: Panel Analysis (no o, d fixed effects)

	(1)	Import Drug Confiscations 2011-2016			
		(2)	(3)	(4)	(5)
	First-stage: Log Immigrants	OLS: dummy	OLS: log value	2SLS: dummy	2SLS: log value
Predicted immigration, 1991-2001	0.0955***				
	(0.0296)				
Predicted immigration, 2001 to t	0.107***				
	(0.0132)				
Predicted immigration 1991-2001, squared	-0.00347***				
	(0.000942)				
Predicted immigration 2001 to t, squared	-0.000830***				
	(0.000108)				
Log Immigrants		0.101***	1.402***	0.191***	2.756***
		(0.00931)	(0.143)	(0.0185)	(0.286)
Observations	72540	72540	72540	72540	72540
Origin-Year FE	Y	Y	Y	Y	Y
Dest.-Year FE	Y	Y	Y	Y	Y
Origin-Dest. FE	N	N	N	N	N
1st-stg F-stat.	54.6			54.6	54.6

Standard errors clustered two-ways at the year-province and origin-destination levels in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Effect of Immigrants on Import Confiscations: Panel Analysis (with o, d fixed effects)

		Import Drug Confiscations 2011-2016			
	(1)	(2)	(3)	(4)	(5)
	First-stage: Log Immigrants	OLS: dummy	OLS: log value	2SLS: dummy	2SLS: log value
Predicted immigration, 2001 to t	0.0307^{***}				
	(0.00523)				
Predicted immigration 2001 to t, squared	-0.000232^{***}				
	(0.0000453)				
Log Immigrants		0.0429^{***}	1.403^{***}	0.326^{***}	4.554^{***}
		(0.0156)	(0.144)	(0.0815)	(1.118)
Observations	72540	72540	72540	72540	72540
Origin-Year FE	Y	Y	Y	Y	Y
Dest.-Year FE	Y	Y	Y	Y	Y
Origin-Dest. FE	Y	Y	Y	Y	Y
1st-stg F-stat.	17.2			17.2	17.2

Standard errors clustered two-ways at the year-province and origin-destination levels in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Effect of Immigrants on Re-Export Confiscations: Panel Analysis (no o, d fixed effects)

		Re-Export Drug Confiscations 2011-2016			
	(1)	(2)	(3)	(4)	(5)
	First-stage: Log Immigrants	OLS: dummy	OLS: log value	2SLS: dummy	2SLS: log value
Predicted immigration, 1991-2001	0.0955***				
	(0.0296)				
Predicted immigration, 2001 to t	0.107***				
	(0.0132)				
Predicted immigration 1991-2001, squared	-0.00347***				
	(0.000942)				
Predicted immigration 2001 to t, squared	-0.000830***				
	(0.000108)				
Log Immigrants		0.0115***	0.129***	0.0211**	0.255**
		(0.00304)	(0.0355)	(0.00913)	(0.110)
Observations	72540	72540	72540	72540	72540
Origin-Year FE	Y	Y	Y	Y	Y
Dest.-Year FE	Y	Y	Y	Y	Y
Origin-Dest. FE	N	N	N	N	N
1st-stg F-stat.	54.6			54.6	54.6

Standard errors clustered two-ways at the year-province and origin-destination levels in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Effect of Immigrants on Re-Export Confiscations: Panel Analysis (with o, d fixed effects)

		Re-Export Drug Confiscations 2011-2016			
	(1)	(2)	(3)	(4)	(5)
	First-stage: Log Immigrants	OLS: dummy	OLS: log value	2SLS: dummy	2SLS: log value
Predicted immigration, 2001 to t	0.0307***				
	(0.00523)				
Predicted immigration 2001 to t, squared	-0.000232***				
	(0.0000453)				
Log Immigrants		-0.00569	0.129***	0.0457	0.592
		(0.00834)	(0.0356)	(0.0605)	(0.719)
Observations	72540	72540	72540	72540	72540
Origin-Year FE	Y	Y	Y	Y	Y
Dest.-Year FE	Y	Y	Y	Y	Y
Origin-Dest. FE	Y	Y	Y	Y	Y
1st-stg F-stat.	17.2			17.2	17.2

Standard errors clustered two-ways at the year-province and origin-destination levels in parentheses

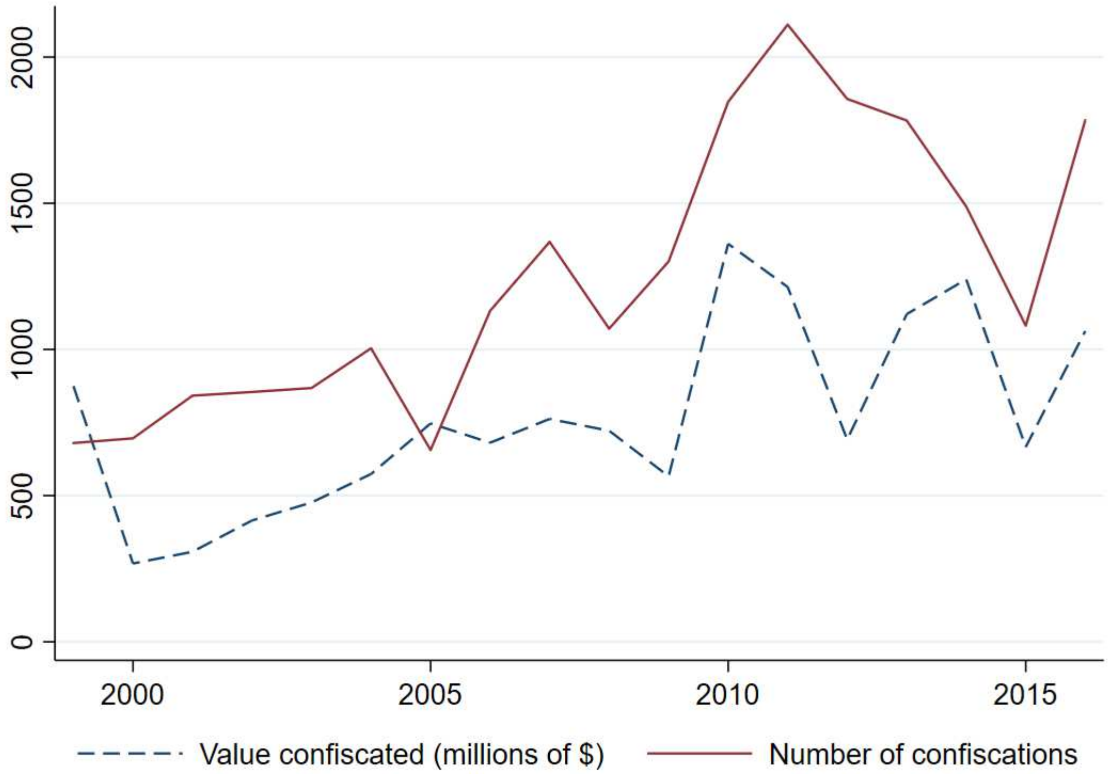
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Effect of Immigrants on Illegal Drug Activity: Province Panel with Leave-Out Instrument

	(1) First-Stage: Log immigrants	(2) 2SLS: Log value confiscated	(3) 2SLS: Log native-born used drugs last 12 mo.	(4) 2SLS: Log native-born ever used drugs
Shift-Share IV	0.159***			
	(0.0413)			
Log Immigrant population		20.23	2.439	5.336
		(12.69)	(2.595)	(4.111)
Observations	728	728	310	312
Kleibergen-Paap F-stat	14.9	14.9	3.3	3.3
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

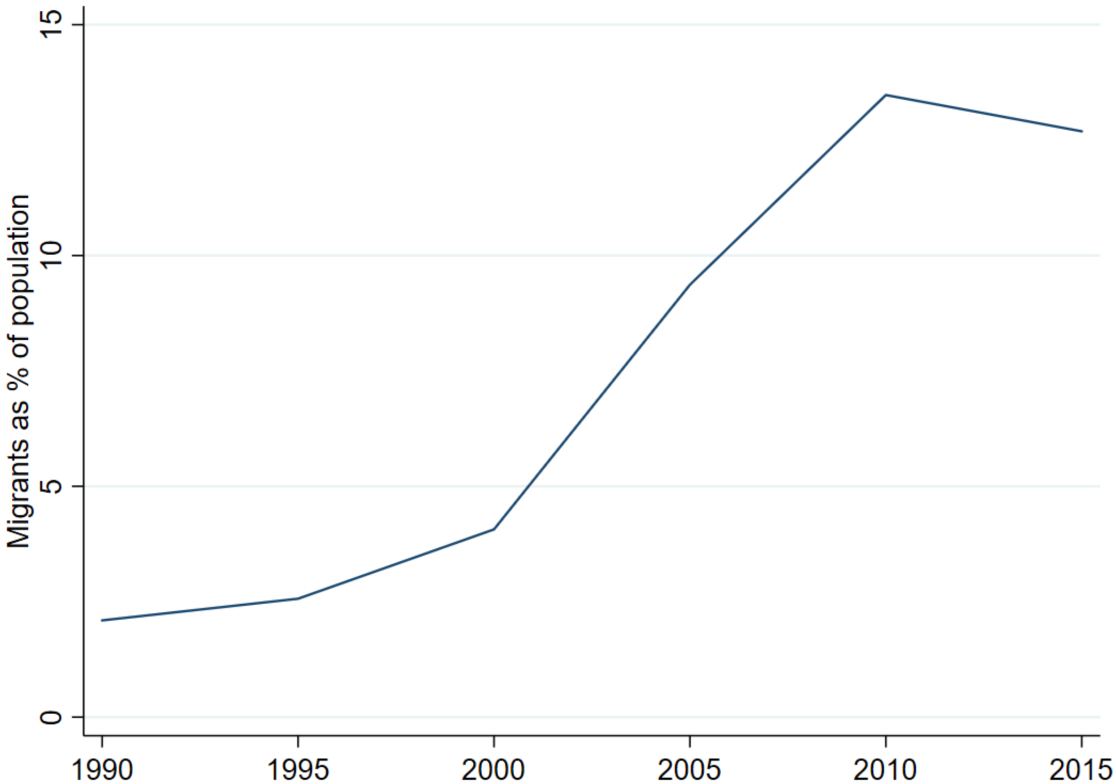
Notes: The table presents coefficient estimates from IV regressions of equation 14 at the province-year level. I instrument for *Log Immigrants* using the excluded instrument defined in equation 15, with the first-stage shown in column 1. In column 2, the dependent variable is the log of 1 plus the value of illegal drugs confiscated as measured in the UNODC Individual Seizures Data. 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). Standard errors are clustered at the autonomous community-by-year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure A.9: Illegal Drug Confiscations per Year, 1999-2016



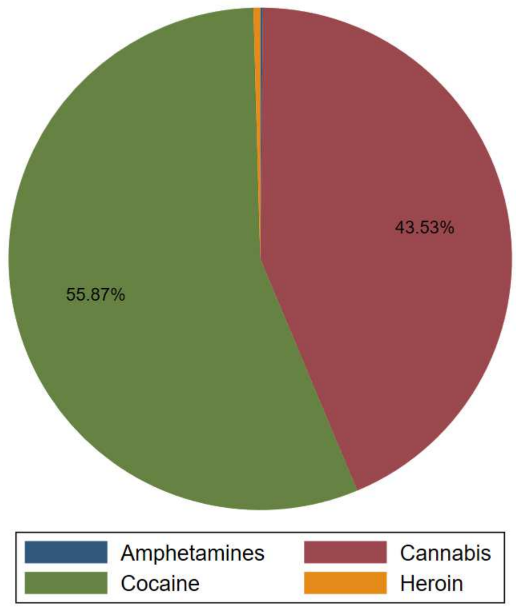
Notes: This figure shows the value of drugs trafficked from foreign countries confiscated over time by Spanish authorities and the number of confiscation events as reported to the United Nations Office of Drugs and Crime (UNODC). Drug prices used are 2012 wholesale prices taken from a survey of Spanish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

Figure A.10: Immigrant Population Share in Spain, 1990–2015



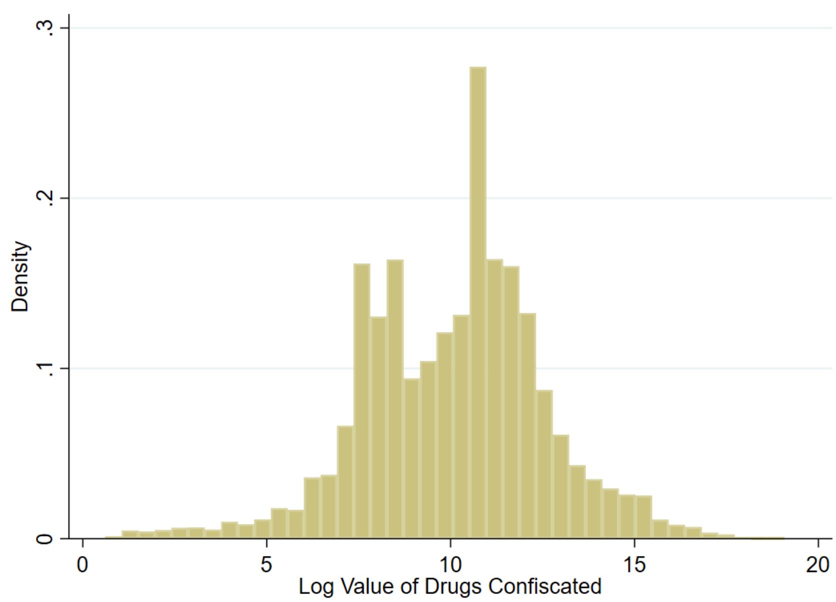
Notes: This figure shows the fraction of the Spanish population born in another country over time. The data are reported by the World Bank but originally come from the United Nations Population Division.

Figure A.11: Confiscations by Drug Type



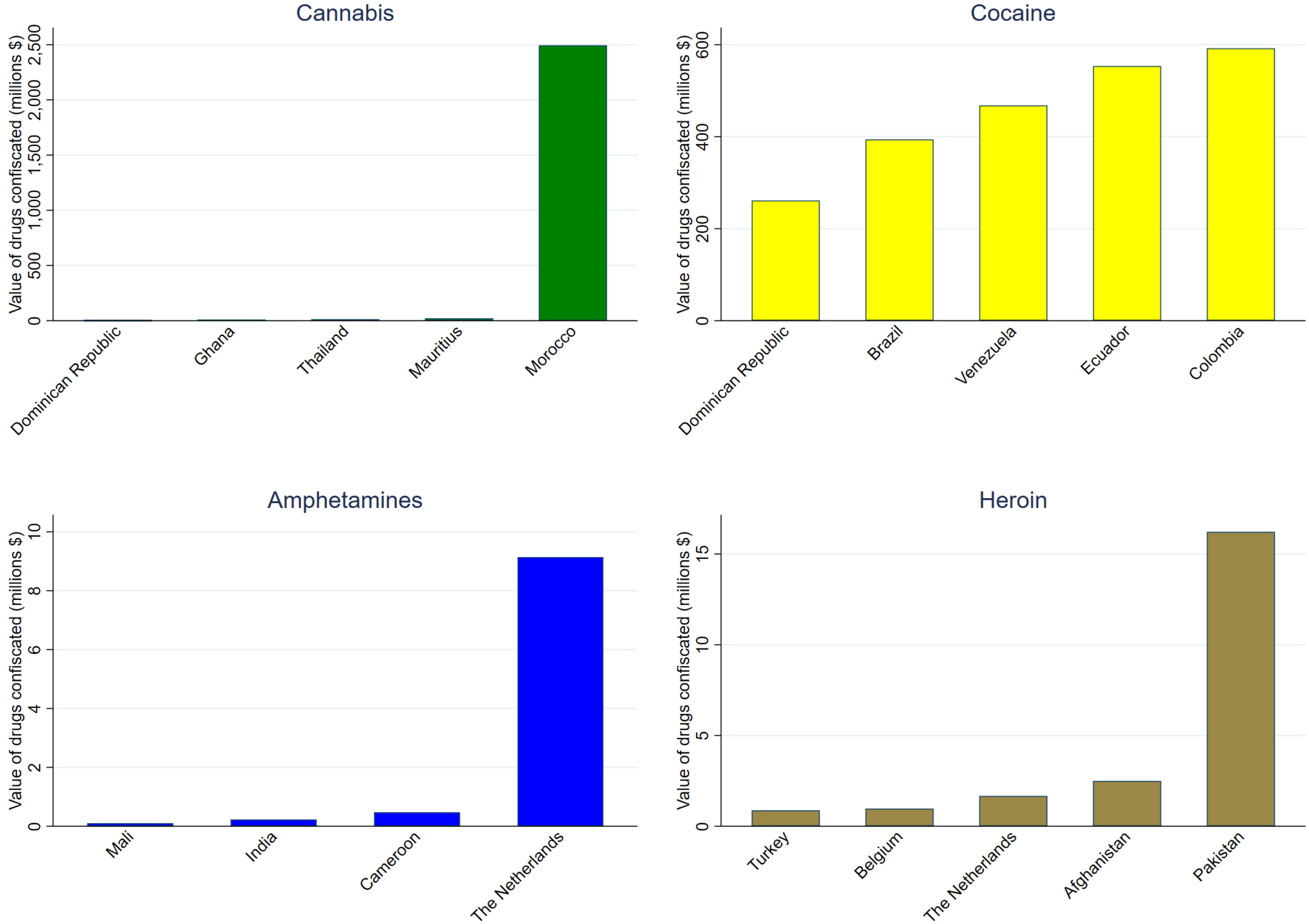
Notes: This figure shows the makeup of drug confiscations in Spain by drug type. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the United Nations Office of Drugs and Crime (UNODC).

Figure A.12: Distribution of Log Value of Confiscations



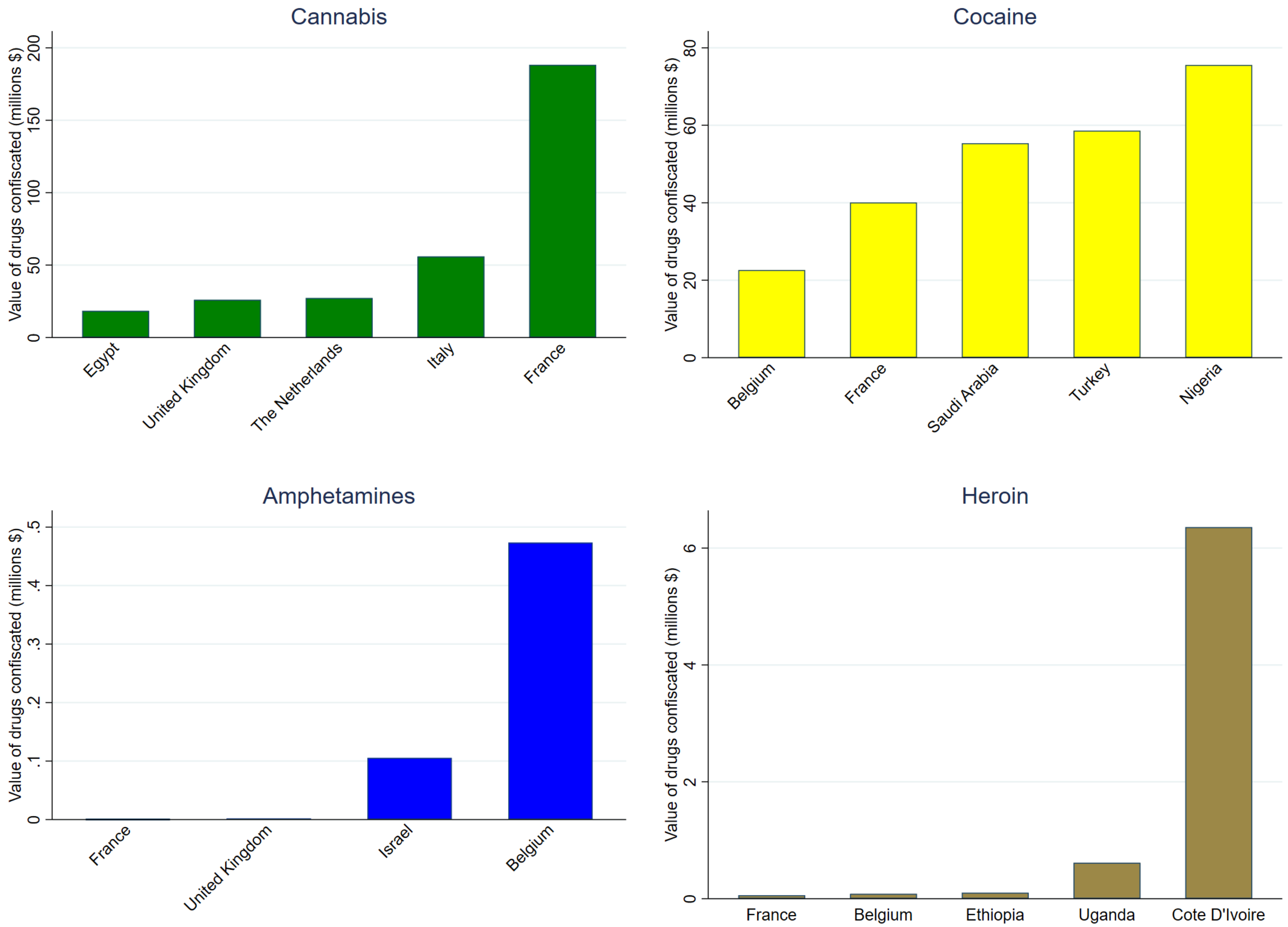
Notes: This figure shows the distribution of the log value of drug confiscations in Spain between 2011 and 2016 as reported to the United Nations Office of Drugs and Crime (UNODC). Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure A.13: Top Five Origins by Drug



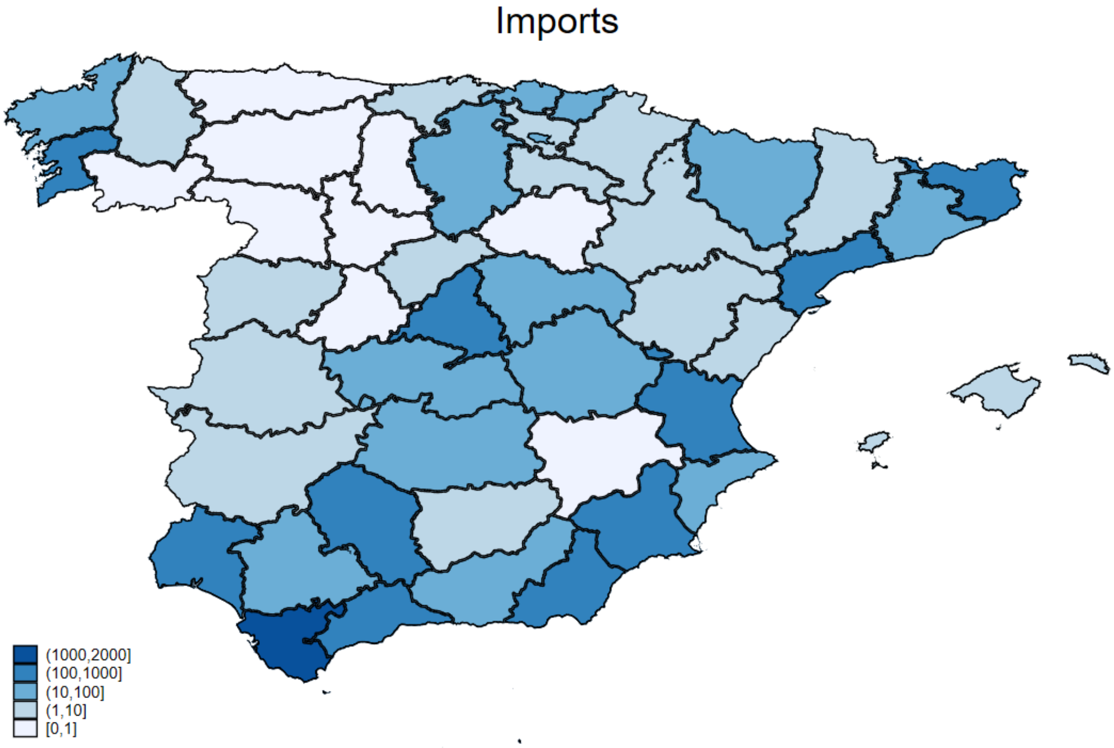
Notes: This figure shows the top five exporters of illegal drugs to Spain during 2011 through 2016 by drug as proxied by confiscations by Spanish law enforcement reported to the United Nations Office of Drugs and Crime (UNODC).

Figure A.14: Top 5 Intended Destinations by Drug



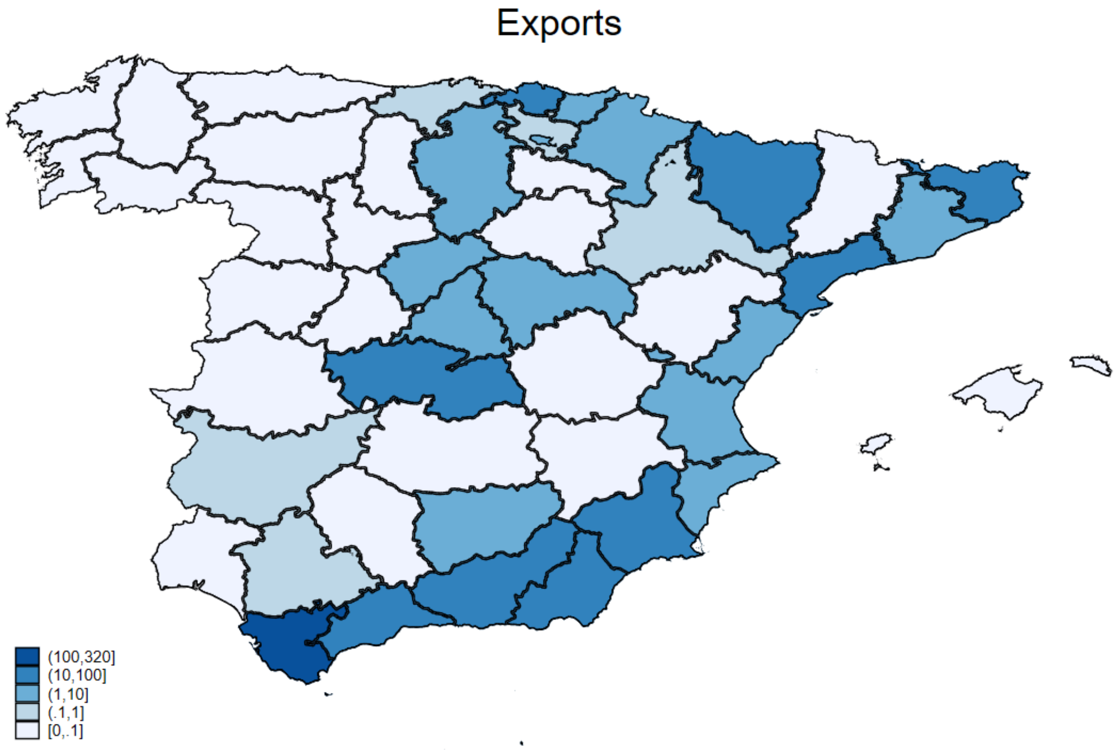
Notes: This figures shows the top 5 importers of illegal drugs from Spain during 2011 through 2016 by drug as proxied by confiscations by Spanish law enforcement reported to the United Nations Office of Drugs and Crime.

Figure A.15: Geography of Drug Import Confiscations in Spain



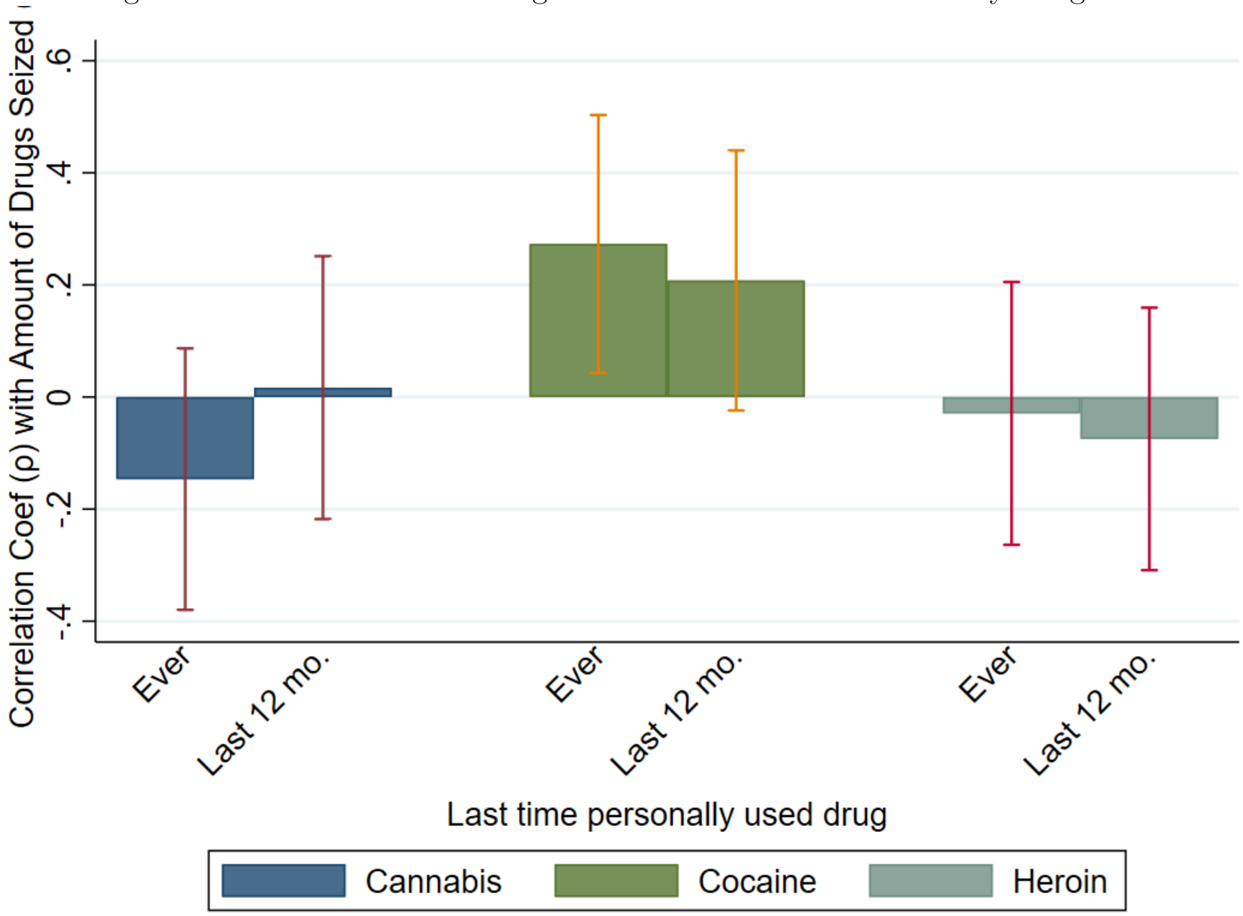
Notes: This figure shows the distribution of drug confiscations of imports (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office of Drugs and Crime.

Figure A.16: Geography of Drug Confiscations Intended for Re-Export in Spain



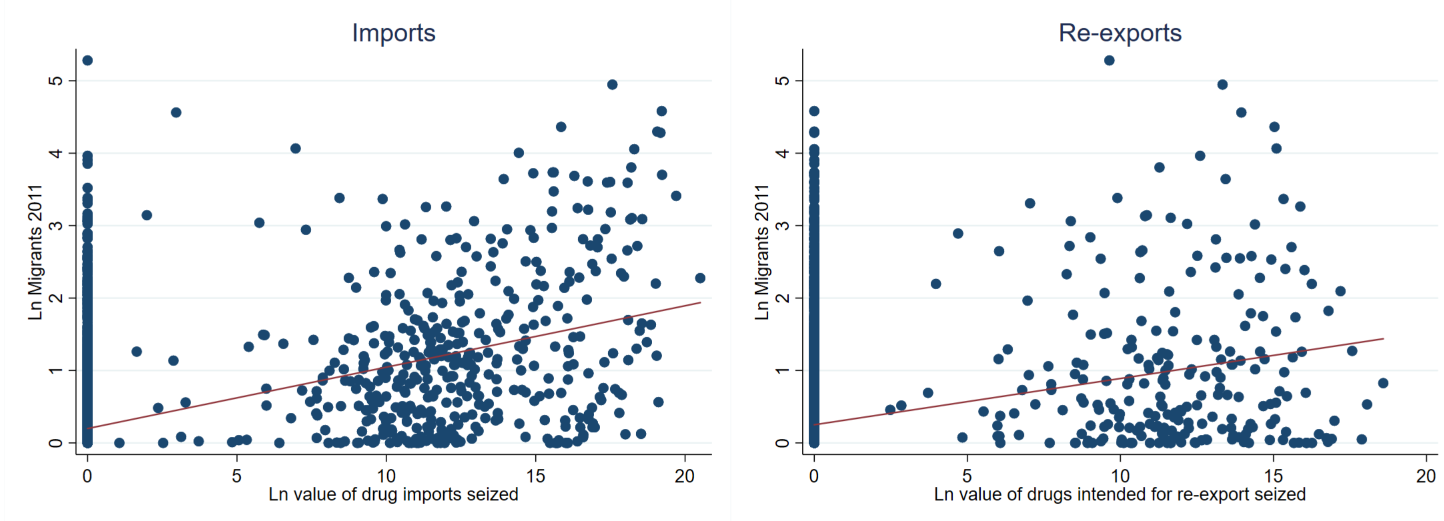
Notes: This figure shows the distribution of confiscations of drugs intended for re-export (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office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

Figure A.17: Correlation of Drug Confiscations to Personal Use by Drug



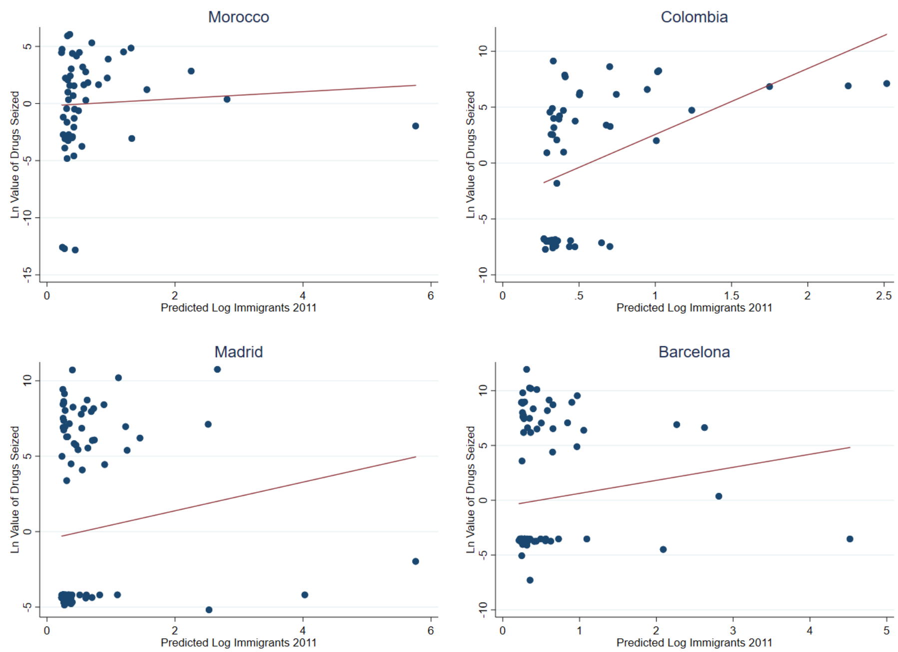
Notes: This figure shows the correlation coefficient between the amount confiscated per capita of a particular drug with the fraction of respondents in a province who report having ever used the drug or having used the drug within the last 12 months averaged over the 2011, 2013, and 2015 waves of the EDADES (Survey on Alcohol and Drugs in Spain) 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 A.18: Drug Confiscations and Number of Immigrants Raw Correlation



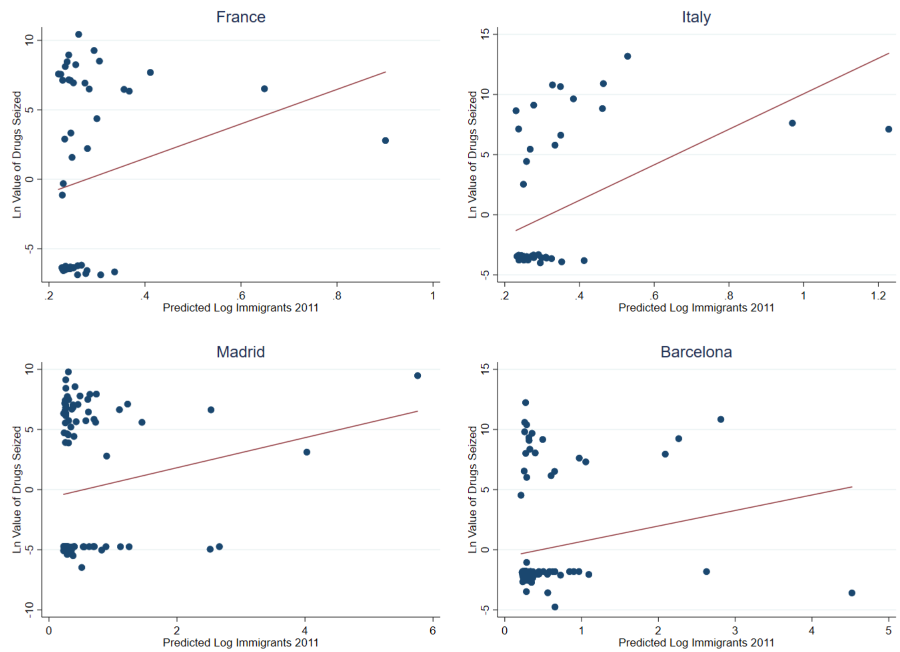
Notes: The figure on the left shows the unconditional scatter plot of the bilateral log value of drug imports confiscated on the x-axis with the bilateral log number of immigrants measured in 2011 on the y-axis. The figure on the right is the same but plots the log of one plus the value of drugs confiscated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

Figure A.19: Migrants and Drug Trafficking Imports



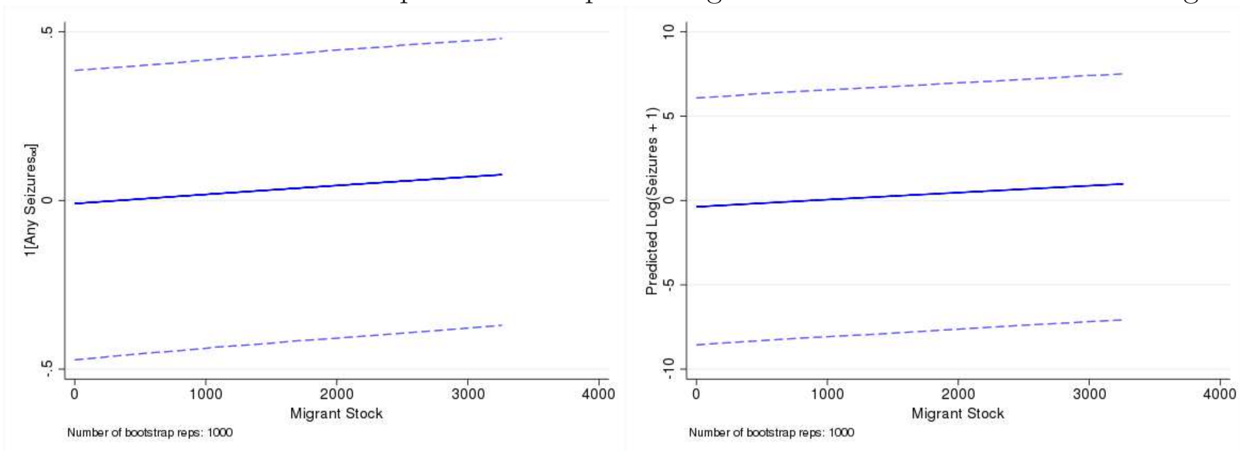
Notes: The figure shows the conditional scatter plots of predicted *Log Migrants* 2011 with the log value of imported drugs confiscated for origins Morocco and Colombia and separately for provinces Madrid and Barcelona. Data are conditional on origin and destination fixed effects and log distance.

Figure A.20: Migrants and Drug Trafficking Exports



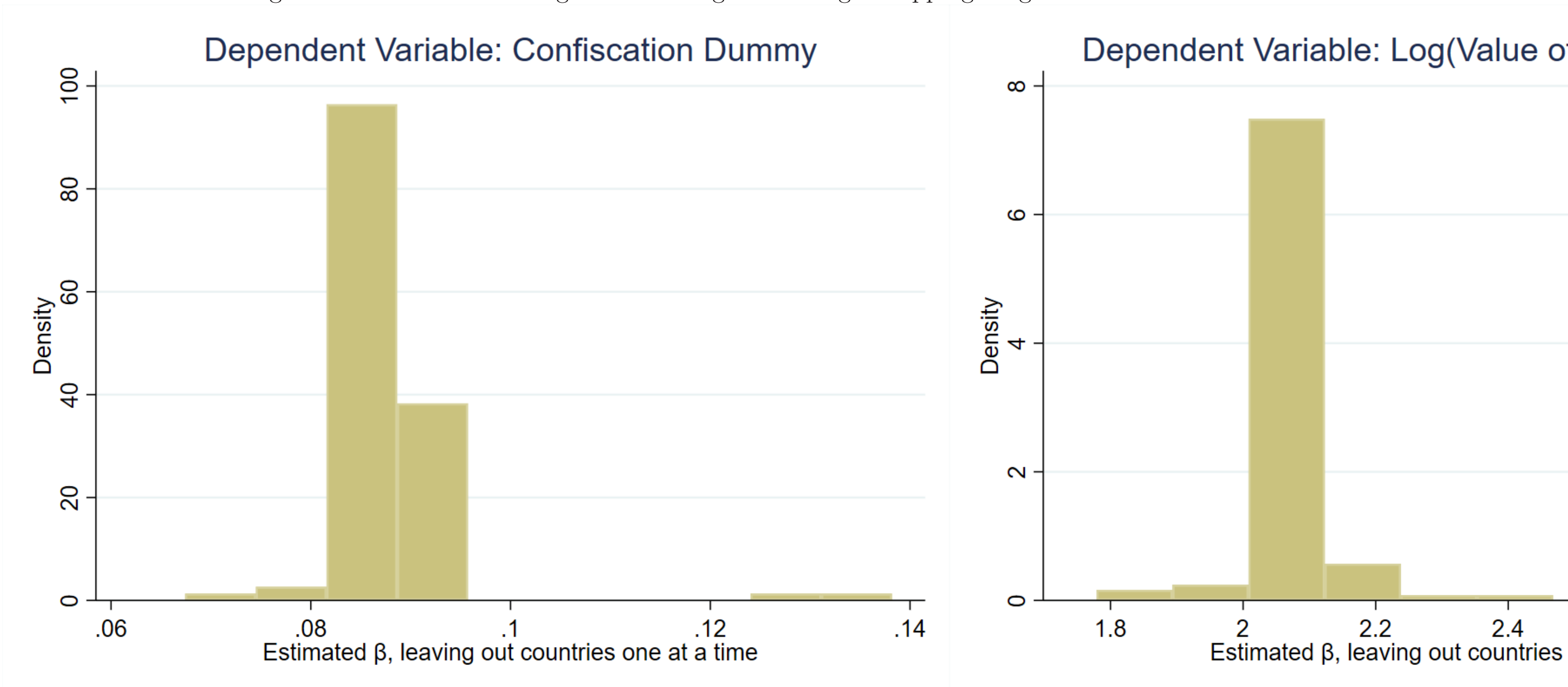
Notes: The figure shows the conditional scatter plots of predicted *Log Migrants* 2011 with the log value of imported drugs confiscated for origins France and Italy and separately for provinces Madrid and Barcelona. Data are conditional on origin and destination fixed effects and log distance.

Figure A.21: Non-Parametric Relationship between Import Drug Confiscations and Bilateral Immigrant Population



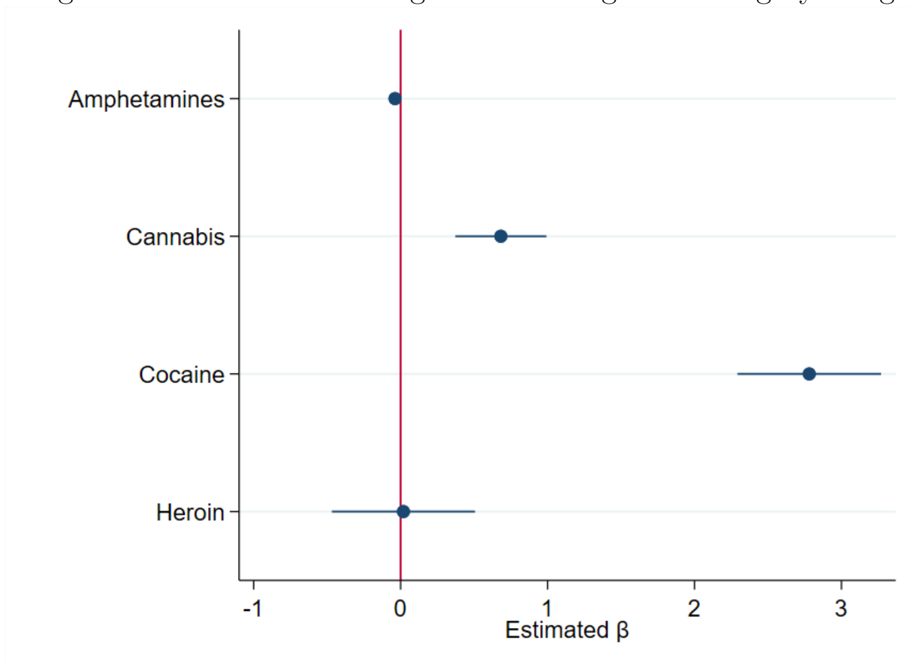
Notes: This figure shows the values of the dummy variable $\mathbf{1}\{S_{od} > 0\}$ (left) or $\log(S_{od} + 1)$ (right) predicted from the non-parametrically estimated function $g(M_{o,d})$, as in $f(S_{o,d}) = \alpha_o + \alpha_d + g(M_{o,d}) + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d}$. S_{od} is equal to the value of drugs confiscated in province d originating from country o. For estimation I used the Stata program `npiv` developed by Chetverikov et al. (2018).

Figure A.22: 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 2) when leaving out one nationality at a time. The figure on the left shows the distribution of βs when the dependent variable of equation 2 is a dummy for whether any drug import from a given origin country was confiscated locally between 2011 and 2016. The figure on the right shows the distribution of β's when the dependent variable is the log of one plus the value of drugs imported from a given origin country and confiscated locally between 2011 and 2016.

Figure A.23: Effect of Immigrants on Drug Trafficking by Drug



Notes: The figure shows the effect of immigrants on drug trafficking (β from equation 2) for the four drugs included for the baseline estimation. As shown in Figure A.11, cannabis and cocaine make up the vast majority of illegal drugs confiscated by Spanish authorities.

Figure A.24: Binscatter, Any Confiscation on Bilateral Immigrant Population

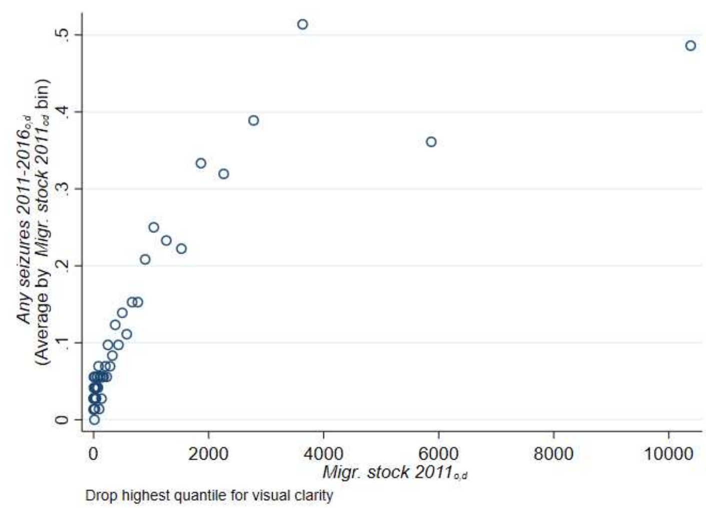
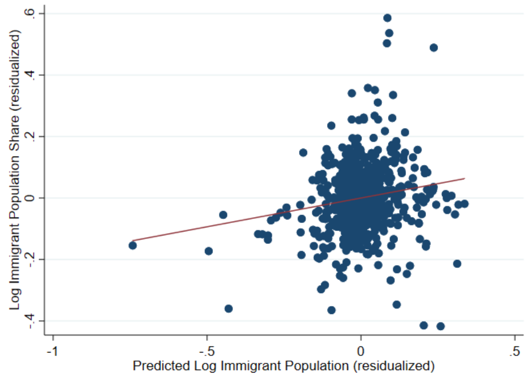
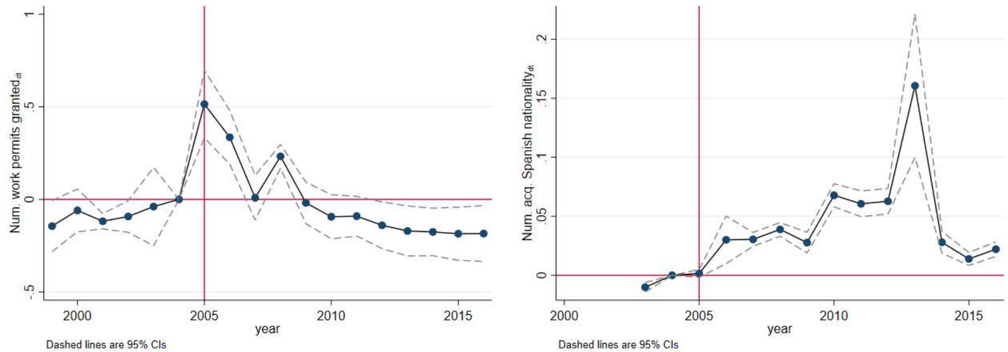


Figure A.25: First-Stage Fit, Province-Level Panel



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 A.26: Effect of 2005 Immigrant Regularization on Work Permits, Naturalizations



Notes: The figure shows event study plots of the effect of the 2005 immigrant regularization on the number of residency permits granted to immigrants (chart on the left) and the number of immigrants obtaining citizenship (chart on the right). Plots are estimated using equation 20. The large spike in citizenship acquisitions in 2013 was caused by a concerted effort by the Spanish government to reduce delays in processing citizenship applications.