Immigrants, Legal Status, and Illegal Trade

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Abstract

Nearly $2 trillion worth of illegal goods are trafficked across international borders per year, generating violence and other social costs along the way. Some have controversially linked this trafficking to immigrants, but even if true the optimal 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 (i) total immigrant inflows into Spain by origin country and (ii) the fraction of immigrants inflowing into a province. I find that a 10% larger population of immigrants from a given foreign country relative to the mean raises the value of drugs from the foreign 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 legalizing immigrants and providing a path to citizenship diminishes the role immigrants play in drug trafficking.

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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 (Matrix Knowledge Group, 2007).

One controversial but untested opinion holds that immigrants, particularly those without legal status, facilitate the trafficking of illegal goods from the immigrants' home country to their host region.[1] 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 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. 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 the acquisition of citizenship by the immigrants.

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 difficult. Second, other factors (such as geography) may affect both the distribution of immigrant populations and illegal drug traf-

[1]Several notable politicians have offered this opinion. 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.

ficking.

To make progress on the difficulty in measuring illegal drug trafficking, I use detailed data on drug confiscations which include information on which country the drugs were trafficked from. In particular, I use a database of individual drug confiscations compiled by the United Nations 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.

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 legal residency permits allows for a straightforward estimation of the irregular immigrant population (González-Enríquez, 2009; Gálvez Iniesta, 2020).

To make progress on causal identification, I borrow an empirical approach from the literature on international trade which exploits variation in trade flows between regions. In particular, I estimate a gravity equation of drug trafficking on the number of immigrants from a given 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. In the context of an illegal good, these fixed effects allow me to control for law enforcement activity directed at drug trafficking specific to each country and Spanish province.

Because immigrants and drugs from a given country may flow to a given Spanish province due to some third factor, such as geography, 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 an origin country o are likely to settle in a 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 the 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 from a given origin country relative to the mean raises the likelihood of a confiscation of illegal drug trafficking from the origin country occurring by 0.5 percentage points and the value of imported drugs confiscated by 12%. Similarly, a 10% increase in the number of immigrants from a given origin country relative to the mean raises the likelihood of a confiscation of drugs intended for re-export to the immigrants' home country by 0.4 percentage points and the value of drugs intended for re-export by 7%.

Next, I assess the extent to which immigrant legal status can explain my baseline results. To do so, I modify my baseline gravity specification by including separate terms for the number of immigrants with and without legal status. I find that the baseline estimate of the effect of immigrants on drug trafficking is driven entirely by irregular immigrants.

The baseline gravity equation 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. I also use a gravity specification similar to my baseline to analyze the impact of immigrants on legal trade and find magnitudes comparable to what I find for illegal drug trafficking.

I argue that the social connections of immigrants to their origin country primarily drives the bilateral immigrant-trafficking relationship that I estimate. Net of the origin and destination fixed effects and differential immigrant selection, immigrants may raise bilateral trafficking of illicit drugs for two reasons. First, 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 the native-born and immigrants raise re-exports at similar magnitudes as they raise imports. Second, immigrants may reduce bilateral trade costs between origin and destination through their social connections to their origin country. Due to the absence of evidence on immigrant preferences driving my results, I rule-in the trade cost explanation.

A competing explanation for my baseline results is that the intensity with which law enforcement conduct 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. I first quantitatively rule out that changes in enforcement intensity in response to more immigrants could explain my baseline effect size. Second, I exploit the fact that for country-province pairs that I predict to be near the extensive margin of trafficking illegal drugs, enforcement changes caused by variation in the number of immigrants do not drive confiscations. The estimates do not differ substantially from my baselines results.

I also find that general equilibrium responses, including changes in the participation of the native-born in drug markets, do not 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 increasing the immigrant population in a province (across all origin countries) raises the value of drugs confiscated locally.

Because unobserved characteristics of the composition of the immigrant population may drive selection into both illegal status and drug trafficking, I exploit a major immigrant regularization program implemented in 2005. This program resulted in nearly half a million immigrants receiving legal status. The program 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 the immigrant's country of origin.

I find that the 2005 mass immigrant regularization reduced drug trafficking significantly shortly after immigrants became eligible to become Spanish citizens. The lack of an immediate effect of regularization on drug trafficking is consistent with Pinotti (2017), as the program-eligible immigrants had pre-existing attachment to the formal labor market. A back-of-the-envelope calculation suggests that the 2005 regularization reduced drug confiscations by up to 20 percent.

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 that generate this relationship. 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 bilateral drug confiscations. They consistently find that immigrant population is positively associated with drug trafficking. However, their analyses have three limitations relative to the present study. First, they do not use exogenous variation in immigrant populations, which may bias their results if unobserved bilateral factors, such as geography or cultural ties, drive both migration and smuggling. Second, they do not include origin or destination fixed effects, so unobserved country-specific factors may similarly cause omitted variable bias. Third, their analyses are at the country-pair level rather than the country-province level. Thus, even if they had included fixed-effects, unobserved national policies vis-a-vis a partner country may still bias the results. Finally, their analyses do not explore the mechanisms (including the role of legal status) that drive the immigrant-trafficking relationship that they estimate.

A key distinction between past studies on the economics of drug trafficking and the present paper is that I look at a *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.

I also provide evidence for a new mechanism linking immigration and crime: immigrants' social connections to their home country. Prior research on immigration and crime tends to focus on the labor market opportunities available to immigrants (Bell et al., 2013; Spenkuch, 2014; Pinotti, 2017; Freedman et al., 2018). I 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 extend the literature on the effects of globalization to illegal markets. Most related is the literature estimating 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). However, none of the existing studies assessed the role that immigrants play in facilitating *illegal* trade.

Finally, I 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. 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 misinvoicing of cultural goods and Akee et al. (2014) estimates the determinants of human trafficking.

This paper proceeds as follows. Section 2 introduces the data, some stylized facts about drug trafficking, 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

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 at the province-level. I find that more confiscations correspond to more drug use and availability.

2.1 Background

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 (p. 30 UNODC, 2020).

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 stressed the importance social ties. Notably, most recruiting of workers in the drug trafficking business took place within one's social network.[2] Traffickers also noted examples in which shared nationality raised trust between individuals seeking to conduct illegal trade transactions[3], and proximity to immigrants from a variety of drug source countries reduced search costs.[4] 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.

2.2 Drug Trafficking Data Description

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.[5] Similarly,

[2]"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)

[3]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)

[4]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)

[5]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 type of drug, 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 list the intended destination country of the confiscated drugs.

I primarily utilize confiscations reported by Spain.[6] These data are compiled in Spain's Statistical System of Analysis and Evaluation on Organized Crime and Drugs (SENDA), 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 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 country in which they were produced). For some drug interdictions, assignment of origin and destination country is fairly straightforward. For drugs confiscated from airline passengers upon arrival at an airport, the origin country is the passenger's departure country and destination country is the passenger's ultimate destination on their travel itinerary. For drugs confiscated from cargo ship containers, a range of documents are checked for country of origin and intended destination, including the bill of lading, the commercial invoice, the certificate of origin, customs clearance forms, and the relevant letter of credit. In the case of "narco-boats" that transport hashish resin in the Strait of Gibraltar, their country of origin is considered to be Morocco unless proven otherwise.

For less straightforward cases, such as the case of drug gangs transporting cocaine intercepted in the Atlantic Ocean off the Galician coast, the country of origin and destination is

[6]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.1) 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.

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 outside an airport or port, the country of origin of the drugs will be determined on the basis of the investigation that is carried out, including any statements made by the arrested person. [7]

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.[8]

Four facts emerge when looking at the data. First, nearly all drugs confiscated by Spanish authorities are cocaine or cannabis, with negligible amounts of amphetamines and heroin as shown in Figure A.3. Second, the distribution of drug confiscation amounts is right skewed as shown in Figure A.4, 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.5 and exports drugs primarily to the rest of Europe and the Medterranean region . Finally, there is substantial spatial variation across Spain the import and export of illegal drugs, as shown in figures A.7 and A.8.

2.3 Validation Exercise

I now 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. This is true for cocaine and heroin, which are produced almost exclusively in Latin America and Asia (p. 21, UNODC, 2016). Cannabis can be produced locally, but confiscations of domestic cannabis plants (Alvarez et al., 2016) are quite small in comparison with 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.[9] Note that many drugs may be re-exported to other provinces within Spain, which will modulate the estimated correlation.

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

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

[8]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.

[9]See https://www.emcdda.europa.eu/countries/drug-reports/2019/spain_en

Spain, interviewing 20 to 30 thousand persons per survey. Respondents are asked about 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 these responses across the 2011, 2013, and 2015 survey rounds as a measure of province-level drug use and drug availability.

I find that confiscations of illegal drugs positively correlate with a wide range of measures of local drug availability. In Figure 1, I plot the correlation coefficient between reported ease or difficulty obtaining a particular drug within 24 hours and the amount of that drug that was confiscated in the province per capita between 2011 and 2016.[10] Consistent with confiscations corresponding to real flows of illicit drugs, I find that the higher the fraction of respondents declaring it "impossible" to obtain a particular drug, the less of that drug are confiscated in the province. 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 Spain (UNODC, 2014).

I also find that confiscations are weakly correlated with respondents' personal drug use history, as shown in Figure A.9. 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.[11]

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

[10] 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.

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

3 Bilateral Empirical Analysis

I seek to understand whether immigrants facilitate drug trafficking between their origin country and their new home province—that is, bilaterally. To do so, I relate bilateral drug confiscations to bilateral immigrant population in a gravity equation, which allows me to control for observed and unobserved characteristics of the origin and the destination. Because migration and drug trafficking may be jointly determined by other factors, such as geographic or climatic similarity between origin and destination, I generate exogenous variation in bilateral immigrant population using an instrumental variables strategy.

While there exists a positive correlation between the number of immigrants and the value of drugs confiscated at the bilateral level as shown in Figure A.10, this may be driven by other factors, such as origin- or destination-specific instritutions or economic development, or bilateral-specific factors. As an example of the relationship which I explore with greater rigor in Section 3.1, I 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, as shown in Figure 3. To more formally evaluate the relationship between bilateral immigrant population and drug trafficking, I estimate this relationship using a gravity equation in the context of Spain.

3.1 Gravity Regression

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

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

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

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.

Given complete information, I would estimate gravity equation of the form[12]

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

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

where α_o and α_d are origin and destination fixed effects, $Dist_{o,d}$ is the distance in kilometers between o and d taken from Peri and Requena-Silvente (2010), $M_{o,d}$ is the number of immigrants from o living in d, usually defined as the log of 1 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 3.6.1), and the error term $\tilde{\varepsilon}_{o,d}$ includes all omitted bilateral forces which may shape drug trafficking. I measure the bilateral immigrant population $M_{o,d}$ using the 2011 Spanish Census distributed by Minnesota Population Center (2019).

Plugging in equation 1, I obtain

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

where $\varepsilon_{o,d} = \tilde{\varepsilon}_{o,d} + \ln(E_{o,d})$. Because drug confiscations are conducted locally, and therefore reporting practices may vary at the local level, I cluster standard errors at the province level.

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, national law enforcement priorities, and so on. Similarly, the destination fixed effect α_d similarly controls for factors of province d common across origins, such as the province's police force strength and the economic conditions in d.

For the empirical analysis, I replace the dependent variable $\ln S_{o,d}$ with $\ln(1 + S_{o,d})$ to avoid dropping bilateral links with no confiscations, as these make up more than half my sample. I also estimate the immigrant-trafficking relationship using a dummy for whether any confiscation occurred as a dependent variable.

I also explore how the number of immigrants affects the re-export margin of drug trafficking. For such an exercise, I consider drugs confiscated in d but which were intended to go to country o.[13] The dependent variables $Y_{o,d}$ I consider are a dummy for whether any confiscation of drugs intended for re-export occurred, $\mathbf{1}\{S_{d,o} > 0\}$, and the log of 1 plus the value of confiscations of drugs intended for re-export, $\ln(1+S_{d,o})$. Hence, my baseline gravity equation is

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

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

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. The OLS 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.

3.2 Instrumental Variable Approach

There may be unobserved factors driving both migration and drug trafficking, such as geographic or climatic similarity. To purge this potential confounding variation from bilateral immigrant populations, I adapt a leave-out push-pull instrumental variables approach to my setting.

Consider, for example, Moroccan immigrants settling in the province of Alicante may be drawn by its similar Mediterranean climate. Additionally, drug traffickers who are skilled at piloting boats in the waters off the coast of Morocco will also 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 instruments for bilateral immigrant population using a set of leave-out push-pull instruments. These instruments produce exogenous variation in bilateral immigrant inflows. I use two decades of inflows between 1991 and 2011 to predict the current bilateral immigrant population. During this period the share of immigrants in Spain's population rose from below 1 percent to well over 10 percent as shown in Figure A.2, 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)

The intuition of the instrument is that a social connection, in this case a migration decision, between and 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.[14]

However, if immigrant inflows are correlated between similar origin countries or between similar Spanish provinces or if bilateral migration is a large share of migration to d or from o, then predicting bilateral flows between o and d using equation 3 would fail the exclusion restriction. 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, both Algerian and Moroccan migration to Alicante may be both jointly predicted by a third factor, climate, which may also affect drug trafficking (for example, 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

$$IV^{D}_{o,d} = I^{D}_{o,-a(d)} \times \frac{I^{D}_{-c(o),d}}{I^{D}_{-c(o)}} \tag{4}$$

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.

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.

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.

[14]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.

I show the regression coefficients of the first-stage in column 1 of Table 2. Instruments from both decades have a positive and statistically significant coefficient and the first-stage F-statistic surpasses conventional threshold levels.

3.3 Results

Imports 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 bilateral immigrant population on the likelihood of a confiscation of imported drugs on that bilateral link is 0.105 (SE=0.039). This estimate implies that at the mean level of bilateral immigrant population, 933, a 10% increase in the number of bilateral immigrants raises the likelihood that the link will be used for drug trafficking by 0.5 percentage points.[15] Similarly, in column 3, the coefficient estimate on bilateral immigrant population on the log value of drugs confiscated is 2.33 (SE=0.56), which implies that a 10% increase in bilateral immigrant population relative to the mean raises the value of drug imports confiscated by 12%.[16] This is in line with other estimates in the literature examining the effect of bilateral immigrant population on legal trade.[17]

Re-Exports Table 3 shows the estimation results when the dependent variable is confiscations of drugs intended for re-export.[18] Column 2 shows the extensive margin result. The coefficient estimate of the effect of immigrants on the likelihood of a confiscation of imported drugs on that bilateral link is 0.083 (SE=0.021). This estimate implies that at the mean level of bilateral immigrant population, 933, a 10% increase in the number of bilateral immigrants raises the likelihood that the link will be used for drug trafficking by 0.4 percentage points.[19] Similarly, in column 3, the coefficient estimate of bilateral immigrant population on the log value of drugs confiscated is 1.339 (SE=0.34), which implies that a 10% increase in bilateral immigrant population relative to the mean raises the value of drug imports confiscated by

[15] Using $\hat{\beta} = 0.105$ from column 2 in Table 2, we have: $\mathbb{1}\left[S_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 933\right] = 0.105\left(\ln\left(1 + \frac{933\times1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.0049$.

[16] Using $\hat{\beta} = 2.331$ from column 3 in Table 2, we have: $\frac{S_{o,d}^{2011-2016}[M_{o,d}^{2011}=1.1\times933]}{S_{o,d}^{2011-2016}[M_{o,d}^{2011}=933]} - 1 = \exp\left(2.331\left(\ln\left(1 + \frac{1.1\times933}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right)\right) - 1 = 0.116$.

[17] 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%.

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

[19] Using $\hat{\beta} = 0.083$ from column 2 in Table 3, we have: $\mathbb{1}\left[S_{d,o}^{2011-2016} > 0 | M_{o,d}^{2011} = 933\right] = 0.083\left(\ln\left(1 + \frac{933\times1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.0039$.

6.5%.[20]

3.4 Preferences for Drugs and Trade Costs

I argue the bilateral results presented in Section 3.3 are driven primarily by the reduction in bilateral trade costs caused by the social connections of immigrants. After controlling for the institutions and labor market conditions of the host province and origin country, more imigrants may raise imports of illicit drugs for two reasons. First, immigrants may prefer to consume goods from their home country. Second, immigrants reduce trade costs between origin and destination. I argue that immigrant preferences are unlikely to be important in the case of illegal drugs, resulting in immigrant social connections reducing trade costs as the primary mechanism driving my baseline bilateral results.

Preferences of the Immigrants. 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 region. To the extent that these tastes carry over to illicit drugs, more drugs may be trafficked to regions with more immigrants. To the extent that consumers can differentiate drugs trafficked from different origin countries, more drugs may be trafficked along bilateral links which also experience more immigration.

To address this, I compare drug-use between immigrants and the native-born. I find that immigrants consume drugs at a substantially lower rate than native-born Spaniards. 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 marijuana, cocaine, heroin, or amphetamines compared to nearly 35% of the Spanish-born. This suggests that immigrants are not driving increases in the local drug use prevalence. In addition, drugs are unlikely to be differentiable to consumers across trafficking origin.

Trade Costs. Migrants may increase illegal trade in much the same way they raise legal trade. Felbermayr et al. (2015) note that migrant 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, migrant networks raise the cost of opportunistic or cheating behavior by firms within the nationality network, who can be punished for bad behavior by being shunned from business within the network (Rauch and Trindade, 2002). Finally, the qualitative studies summarized in Section 2.1

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

demonstrate ways in which social connections between immigrants can facilitate trafficking by reducing trade costs.

3.5 Drug-Hubness of Origins

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 which are "hubs" of drug trafficking, that is, countries which export large amounts of illicit drugs. To do so, I estimate equation 2 but interact my measure of bilateral immigrants with a measure of the extent to which an origin country is a drug hub, defined as either the fraction of total world drug confiscations coming from the origin country or the rank order thereof.

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, however, is that reporting of drug confiscations to the UNODC is less frequenty and high quality than in Spain. Nevertheless, no alternative data source on country-pair drug trafficking exists so I pursue this analysis using these imperfect data.

In Table A.3 I show the estimated coefficients. I find that origin countries which are significantly involved in drug trafficking, i.e. 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.

3.6 Robustness Checks and Legal Trade

3.6.1 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, with results shown 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.16 of the relationship between the bilateral number of immigrants and the dummy variable for whether any confiscation occurs.

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

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

In equation 5 I estimate (π_1, π_2) whereas in equation 2 I assumed $\pi_1 = \pi_2 = 0.001$. 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 $Y_{o,d} \in \{\ln(S_{o,d}+1), \mathbf{1}\left[S_{o,d}>0\right]\}$ 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 intruments to improve convergence. Including a moment for the constant, this yields 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 occuring on a bilateral link by 1.1 percentage points and the value of drugs confiscated by 20 percent.

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). I depict the results in Figure A.13. 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.

3.6.2 Varying Estimation Sample

Because drug trafficking into Spain is driven by a select few countries–Morocco, for example, is dominant exporter of cannabis to Spain. To see whether any particular origin country drives my baseline results, I re-estimate my baseline specification leaving out individual countries. Figure A.14 shows the distribution of β estimates from equation 2 when I drop one origin country at a time for both dependent variables, $\mathbf{1}\left[S_{o,d} > 0\right]$ and $\ln(S_{o,d}+1)$. 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 type of drug. 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.15. However, heroin and amphetamines represent less than 1% of drugs confiscated by Spain as shown in Figure A.3 and therefore precice estimates are unlikely.

Finally, I consider a selection of high-trafficking countries and provinces alone. In Figure A.11, 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.12, 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.

3.6.3 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. I show estimates using different clustering of standard errors in Table A.4. The estimates mostly remain statistically significant across the different clustering geographies.

3.6.4 Panel Estimation

To see whether my baseline results extend to a longer time-spain as well as if they are robust to controlling for origin-by-destination time invariant characteristics, I extend my estimate a panel specification. In particular, I estimate

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

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

where $Y_{o,d,t} \in \{\mathbf{1}[S_{o,d,t} > 0], \ln(S_{o,d,t}+1)\}$ for the value of drugs confiscated in d from o in year t $S_{o,d,t}$ for both imports and intended re-exports. $M_{o,d,t}$ is measured as the log of bilateral immigrant population in thousands plus 1, where the bilateral immigrant population is derived from annual tabulations taken from Spain's local population registries. 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 which 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.[21]

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.

3.6.5 Legal Trade

To gauge the magnitude of the effect size estimated in Section 3.3 for illegal trade relative to legal trade, I estimate the relationship between bilateral immigrant population and legal trade. To measure legal trade volume I turn to the ADUANAS-AEAT data set provided by the Spanish government. This data provides transaction level data and includes information on the origin (for imports) or destination (for exports) country, and the same for origin or destination province within Spain. I aggregate this 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

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

o and for instrument set

$Z_{o,d} = \left(I_{o,d}^{IV,1991-2001}, I_{o,d}^{IV,2001-2011}, (I_{o,d}^{IV,1991-2001})^2, (I_{o,d}^{IV,2001-2011})^2, (I_{o,d}^{IV,1991-2001} \times I_{o,d}^{IV,2001-2011}) \right)'$.[22]

I show the results in column 2 of Table 4. 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.[23]

4 Enforcement Intensity and General Equilibrium Responses

My bilateral estimates may not imply that overall illegal drug market activity rises with additional migration for two reasons. First, increases in trafficking may be offset by decreases in local production or decreases in imports on other bilateral links. Second, increases in bilateral immigrant population may increase the scrutiny of law enforcement, thus resulting in the relationship estimated in Section 3.3 but not corresponding to a real rise in actual drug flows. I do not find evidence for either of these channels, suggesting that immigrants are in fact raising overall drug imports.

4.1 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 reactions to immigrant-induced trafficking. For example, the native-born may adjust their involvement in drug trafficking in response to immigration. I assess the strength of the general equilibrium response by estimating the effect of immigrants on drug market activity at the province-level.

4.1.1 Province Panel

I first estimate the effect of immigrant population on drug market activity using a panel of Spanish provinces. For the years 2003 to 2016, I estimate

$$\ln Y_{d,t} = \alpha_d + \alpha_t + \beta \ln M_{d,t} + \epsilon_{d,t} \tag{10}$$

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

[22]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.

[23]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 $\frac{X_{o,d}^{2011}[M_{o,d}^{2011}=1.1\times963]}{X_{o,d}^{2011}[M_{o,d}^{2011}=963]} - 1 = \exp\left(1.36\left(\ln\left(1+0.012\times(1.1\times963)\right) - \ln\left(1+0.012\times963\right)\right)\right) - 1 = 0.127$.

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):

$$IV_{d,t} = \ln\left[\sum_{o}\left(\frac{Immigrants_{o,d,1981}}{Immigrants_{o,1981}}\right) \times Immigrants_{o,t}\right] \tag{11}$$

where $Immigrants_{o,t}$ refers to the number of immigrants from o living in Spain in year t.[24]

Because I am exploiting less variation than in my baseline gravity estimation, interpreting β as the causal effect of immigrant share on drug activity requires a stronger identifying assumption, as I am no longer able to exploit variation across immigrant origins. In particular, my identification assumption requires that there are no persistent shocks within autonomous communities which 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.17 I show the first-stage fit. The instrument well predicts immigrant population across Spanish provinces over time.

Drug Import Confiscations. I estimate equation 10 with dependent variable $S_{d,t}$, the log value of drugs confiscated in province d in year t. Column 2 of Table 6 shows the result. I find that a 10% increase in immigrant population share in a province raises drug smuggling into that province by 5% overall. This elasticity of immigrant population to illegal drugs imported is less than my baseline estimates, which suggests general equilibrium adjustment (such as trade diversion) to trafficking by immigrants does occur. However, there still remains an effect of immigrants on drug trafficking.

Native-born Drug Use. I next estimate equation 10 with dependent variable $DrugUsers^{Native}_{d,t}$, 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. This may be because immigrant-induced drug trafficking is mostly re-exported, and therefore not intended for use in the local market.

[24] I also use a jackknife version of equation 11 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.

4.1.2 Province Cross-Section

Next, I estimate the effect of immigrant population on drug market activity using a single cross-section of Spanish provinces. I estimate

$$\ln Y_d = \alpha + \beta \ln M_{d,2011} + \gamma \ln Population_{d,1981} + \epsilon_{d,t} \tag{12}$$

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 use again use the shift-share instrumental variable defined in Equation 11. While some measures of local illegal drug market activity are only available for a single cross-section, a major drawback is the lack of power to estimate the parameter of interest, β.

Native-born Drug Trafficking Arrests. I first estimate 12, measuring illegal drug activity Y_d as the number of native-born 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.

Domestic Production of Cannabis. Finally, I measure illegal drug activity as the log number of cannabis plants confiscated. I draw on Alvarez et al. (2016), who assemble a dataset on cannabis plants confiscations based on press reports and public statements by the Spanish government in 2013.[25] I find that as the local immigrant population increases, there is no effect on the number of cannabis plants confiscated locally. This result suggests that there is little domestic response to changes in immigrant drug trafficking.

4.2 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 strategy controls for enforcement intensity specific to each Spanish province (and common across all origins) as well as 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. In addition, I

[25] 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.

conduct another test for the extent to which enforcement intensity drives confiscations in Appendix B.1.

Quantitative Exercise. First, I consider the plausibility of variation of enforcement intensity explaining the quantitative magnitudes that I estimated in Section 3.1. 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:

$$\frac{dS_{o,d}}{dM_{o,d}} = E_{o,d}\frac{\partial X_{o,d}}{\partial M_{o,d}} + X_{o,d}\frac{\partial E_{o,d}}{\partial M_{o,d}} \tag{13}$$

Dividing equation 13 by the value of drugs confiscated $S_{o,d}$ and multiplying by the bilateral immigrant population, I obtain

$$\epsilon_{S,M} = \epsilon_{X,M} + \epsilon_{E,M} \tag{14}$$

where $\epsilon_{a,b}$ is the elasticity of a with respect to b. In Section 3.1, I estimate $\hat{\epsilon}_{S,M} = 1.2$. Suppose now that actual drug flows are not at all affected by the bilateral immigrant population, i.e. $\epsilon_{X,M} = 0$. To assess the plausbility 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

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.[26] This represents an increase in bilateral immigrant population of 3000%, which would imply 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 comute this as

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

where C_{EU} is the size of the market for illegal drugs in the European Union and S_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.

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

For C_{EU}, I use the European Monitoring Centre for Drugs and Drug Addiction[27] estimate for the size of the market for cocaine and cannabis in the European Union of about $20 billion USD in 2013. I compute $\frac{S_{Spain}}{S_{EU}}$ 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 percent 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 $E_{o,d} \leq 1$.

Extensive Margin of Trafficking. Next, I use the intuition that for bilateral links near the extensive margin of trafficking illegal 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 13, 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

$$\mathbf{1}\{S_{o,d} > 0\} = \alpha_o + \alpha_d + \beta M_{o,d} + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d} \tag{15}$$

for the subset of observations for which I predict that $X_{o,d} \approx 0$.[28]

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:

$$\hat{S}_{o,d} = S_{o,-a(d)} \times \frac{S_{-c(o),d}}{S_{-c(o)}} \tag{16}$$

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

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

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

differently against immigrants from o.

I show results in Table 5 subsetting to bilateral links which 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 that enforcement variation cannot fully explain my bilateral results.

5 Legal Status, Naturalization, and Trafficking

Immigrants' integration into labor markets and civil society may be hampered when immigrants do not have legal status or a path to citizenship. A lack of legal status may hinder immigrants' 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).

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 find that granting immigrants citizenship can significantly reduce drug trafficking.

5.1 Background

In Spain, irregular immigrants are defined as those living in the country without a residency permit. Irregular immigrants generally enter Spain through legal means (González-Enríquez, 2009). These include immigrants who overstay their tourist visas, stay in Spain beyond the terms of their temporary residence permits, and so forth.[29] Moreover, irregular immigration is a common phenomenon in Spain among immigrants. Surveys of immigrants in Spain have found 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.

[29]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).

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. This creates a strong incentive for irregular immigrants to register, a fact which I exploit to measure irregular migration prevalence.[30]

Obtaining legal status puts immigrants on the path to citizenship. Immigrants must live in Spain continuously and legally for 10 years before they can apply for naturalization. For immigrants from Latin America, this requirement drops to 2 years. In addition, immigrants must meet various assimilation and "good citizen" requirements, such as knowledge of the Spanish language and avoidance of crime.

5.2 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

$$Irregular\ \ Migrants_{od} = Population\ \ Registry\ \ Count_{od} - Residency\ \ Permits_{od} \tag{17}$$

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

I do this all 52 provinces in Spain 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.

[30] 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.

5.3 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 to include two separate terms for the bilateral immigrant population by regular and irregular 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 $Y_{o,d}$ is either a dummy for whether any confiscation occurred or the log value of drugs confiscated plus 1.

Separating immigrants by legal status introduces another margin of selection not dealt with by the baseline leave-out push-pull instrument. 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 persistent confounders at the province-country pair level driving selection into both irregular status and drug trafficking.

More concretely, consider the case of Moroccan immigrants living in Barcelona. $m_{o,d}^L$ uses information on the legal status of Moroccan immigrants outside Catalonia (the autonomous community of Barcelona) back in 2003 to predict the 2011 legal status of Moroccans in Barcelona. The exclusion restriction is violated if, for example, Moroccans in Madrid in 2003 were driven into irregularity and drug trafficking by the same confounder (preference for risk-taking, suppose) as 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 Moroccans elsewhere (i.e., it is not absorbed by the Morrocan fixed effect).

Table 8 shows the results for estimating equation 18. I find that a 10% increase in bilateral *regular* immigrant population reduces the likelihood of a drug confiscation by 0.5 percentage points, though the estimated coefficient is statistically insignificant, and a 10% increase in bilateral *irregular* immigrant population raises the likelihood of a drug confiscation by 1.9 percentage points[31] (column 2). A 10% increase in bilateral regular immigrant population raises the value of drugs confiscated by 0.18% (also statistically insignificant), while a 10% rise in the bilateral population of irregular immigrants raises the value of drugs confiscated by 29%[32] (column 4). Taken together, these results suggest immigrant legal status is an important factor shaping immigrants' role in drug trafficking. However, my identification strategy cannot separate between the two channels through which legal status could be operating: that of selection—that certain origin-destination pairs tend to select for more irregular immigrants—and migration policy—the direct effect of legal status on drug trafficking. 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.

5.4 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, offered a work contract of at least 6 months (3 months if in agriculture) and have 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 get a sense for the effect of such a large regularization program on drug trafficking, I do a back-of-the-envelope calculation by combining the estimates from section 5.3 with the estimated fraction of immigrants who are irregular. Using the data and method described in section 5.2, 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 esti-

[31] Using $\hat{\beta}^{Reg} = -0.112$ from column 2 and mean value of bilateral immigrant population of 933, I find that $\mathbb{1}\left[S^{2011-2016}_{o,d} > 0 | M^{2011}_{o,d} = 933\right] = -0.112\left(\ln\left(1 + \frac{933\times 1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.005$ and for $\hat{\beta}^{Irreg} = 0.403$, this is 0.019.

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

mate that the regularization program reduced illegal drug trafficking by about 20%.[33] Note, however, that this back-of-the-envelope calculation assumes no offsetting general equilibrium effects.

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 3.1 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 reflects measurement error. To smooth out this variation and thereby obtain more precise estimates, I aggregate to the province-level. 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, $Y_{d,t} = \mathbf{1}\{S_{d,t} > 0\}$, and the log value of drug confiscations, $Y_{d,t} = \ln(S_{d,t} + 1)$.

I find that the 2005 regularization led to sudden jump in the number of work authorizations granted to immigrants in Spain, as shown in Figure A.18. In addition, naturalizations of immigrants increased markedly in 2005, 2010, and 2013. The 2005 increase is may be related to the 2000 regularization of several hundred thousand immigrants, while the 2010 increase relates to the 2005 regularization under study here. This is consistent with the timeline for naturalization for Latin Americans. The 2013 spike in citizenship granting is due to solving technical and bureaucratic issues which had delayed issuance of citizenship for many immigrants.[34]

In Figure 5 I show the effect of the 2005 regularization on total drug confiscations. Confiscations declined significantly in 2010 and stayed low thereafter. Moreover, this decline came primarily from declines in cocaine confiscations, as shown in Figure 6. This is consistent with the increase in naturalizations for Latin Americans but a modest decline in naturalizations for immigrants from Africa, as shown in Figure 7.

Overall these results suggest that granting legal status to immigrants plays an important

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

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

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 percent.

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 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.

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 migration is an important factor shaping international drug trafficking, on par with the effect immigrants have on legal trade. This effect is driven primarily by immigrants without legal status, and my evidence shows that granting legal status and a path to citizenship to immigrants can significantly diminish this relationship.

These results 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. Amnesty programs are likely to be much cheaper to implement.

An important caveat is that immigrants generate a range of effects on their host countries, from wages of the native-born to innovation to consumer choices. Hence, generalizing welfare effects of immigration from just one outcome, as is the subject of the present study, can lead to suboptimal policy choices. Instead, future researchers and policymakers must weigh the varied impacts of migration when shaping immigration policy.

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Table 1: Effect of Immigrants on Drug Confiscations: OLS

	(1)	(2)	(3)	(4)
	Inbound Drug Confiscations 2011-2016 (Dummy)			
Log Immigrants 2011	0.220***	0.187***	0.205***	0.137***
	(28.70)	(12.52)	(20.71)	(10.54)
Observations	5564	5564	5564	5564
	Outbound Drug Confiscations 2011-2016 (Dummy)			
Log Immigrants 2011	0.0899***	0.114***	0.0613***	0.0609***
	(6.66)	(5.01)	(8.11)	(4.18)
Observations	5564	5564	5564	5564
	Inbound Drug Confiscations 2011-2016 (Log Value)			
Log Immigrants 2011	1.074***	1.393***	0.722***	0.751***
	(5.76)	(4.61)	(7.11)	(4.03)
Observations	5564	5564	5564	5564
	Outbound Drug Confiscations 2011-2016 (Log Value)			
Log Immigrants 2011	1.276*	1.276*	1.276***	1.276*
	(2.36)	(2.00)	(3.78)	(2.66)
Observations	5564	5564	5564	5564
Country FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Log dist	Y	Y	Y	Y

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)	(3) 2SLS: (ln value)
$IV_{o,d}^{2001-2011}$	0.0374**		
	(0.0140)		
$IV_{o,d}^{1991-2001}$	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 $\{IV_{o,d}^{D} = I_{o,-a(d)}^{D} \times I_{-c(o),d}^{D}/I_{-c(o)}^{D}\}_{1991-2001,2001-2011}$ 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)
$IV_{o,d}^{2001-2011}$	0.0374**		
	(0.0140)		
$IV_{o,d}^{1991-2001}$	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 $\{IV_{o,d}^{D} = I_{o,-a(d)}^{D} \times I_{-c(o),d}^{D}/I_{-c(o)}^{D}\}_{1991-2001,2001-2011}$ 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
Shift-Share 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

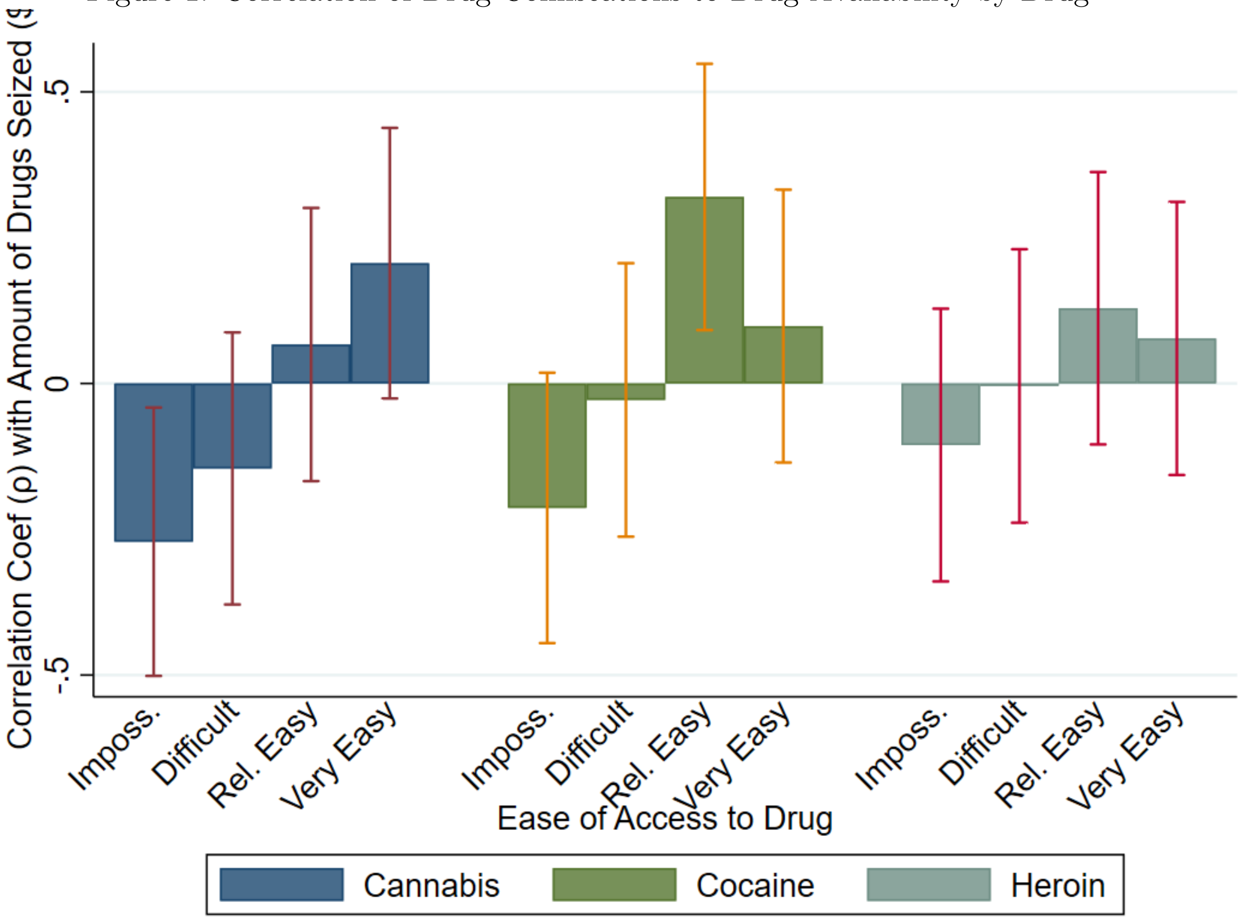
Notes: The table presents coefficient estimates from IV regressions of equation (12) at the province level. I instrument for *Log Immigrants 2011* using the excluded instrument defined in equation (11), with the first-stage shown in column 1. In column 2, the dependent variable is the log of the number 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

	Confiscations of Imported Drugs 2011-2016			
	(1)	(2)	(3)	(4)
	(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
Origin FE	Yes	Yes	Yes	Yes
Dest. FE	Yes	Yes	Yes	Yes
Ln dist	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat.	61.0	8.3	61.0	8.3

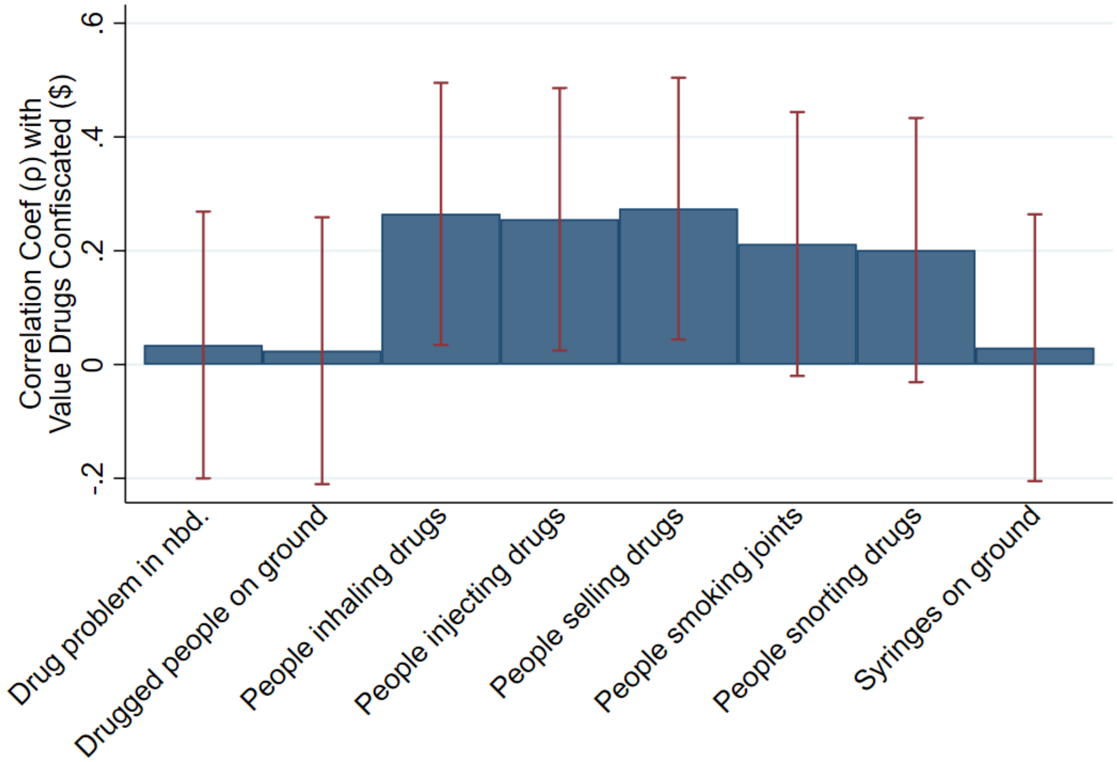
Notes: The table presents coefficient estimates from IV regressions at the country-province level for the set of country-province pairs for which there is data on the irregular immigrant population. In columns 1 and 3, I estimate equation 2 and instrument for *Log Immigrants 2011* using the IV defined in equation 4. In columns 2 and 4, I estimate equation 18 and instrument for regular and irregular immigrant population using the IV defined in equation 19. I present my methodology for estimating the irregular immigrant population in section 5.2. The dependent variable is either a dummy for whether any drugs from country o were confiscated in province d between 2011 and 2016 (columns 1 and 2) or the log of 1 plus the value (in 2012 USD) of drugs from country o confiscated in province d between 2011 and 2016 (columns 3 and 4). All regressions control for country and province fixed effects and log distance. Standard errors are clustered at the province level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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



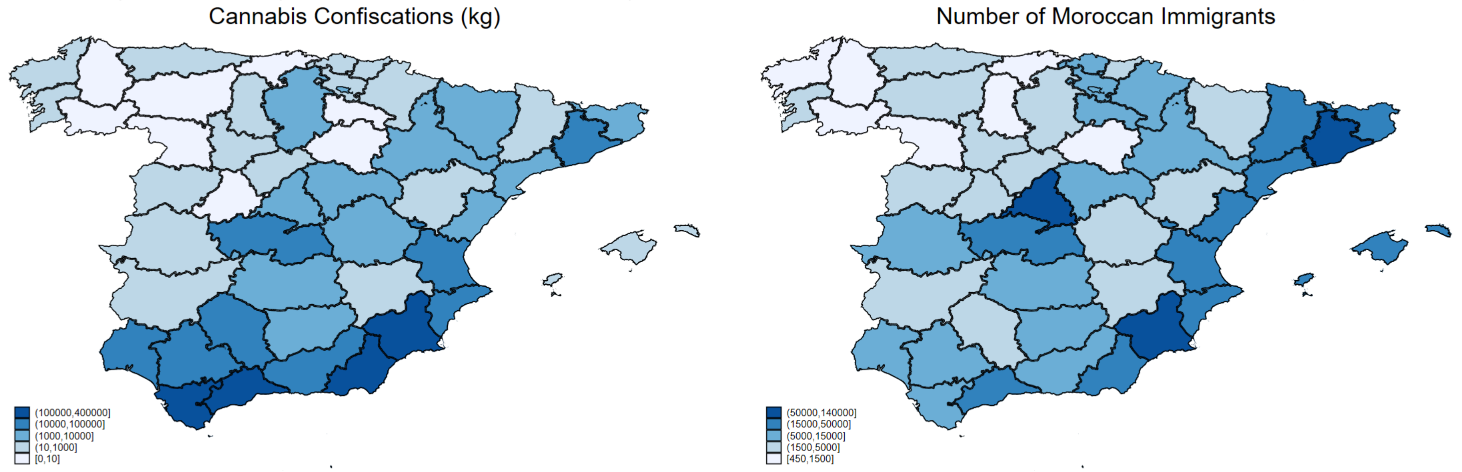
Notes: This figure shows the correlation coefficient between the amount of confiscations per capita of a particular drug with the fraction of respondents in a province who report finding it impossible/difficult/relatively easy/very easy to obtain that drug within 24 hours averaged over the 2011, 2013, and 2015 waves of the EDADES survey. Amphetamines were not asked about until the 2013 survey, so I exclude them. 90% 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)



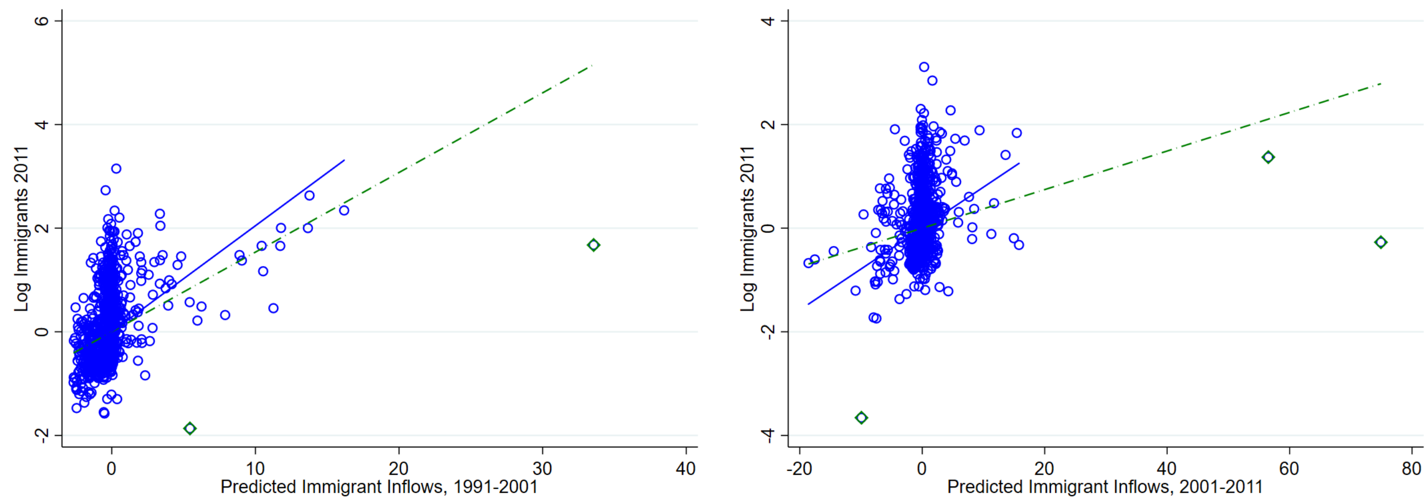
Notes: This figure plots the correlation coefficient between illegal drug confiscations (measured in dollars) per capita across all drugs (as appropriate) with the fraction of respondents in the province who reported observing the listed drug-related behaviors either "frequently" or "very frequently" 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/aluminum?", (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 marijuana from the drug confiscation variable in the correlation, specifically for the questions on people snorting or injecting drugs or syringes being on the ground. 90% confidence intervals are shown in red. Estimated on a cross-section of 52 Spanish provinces.

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



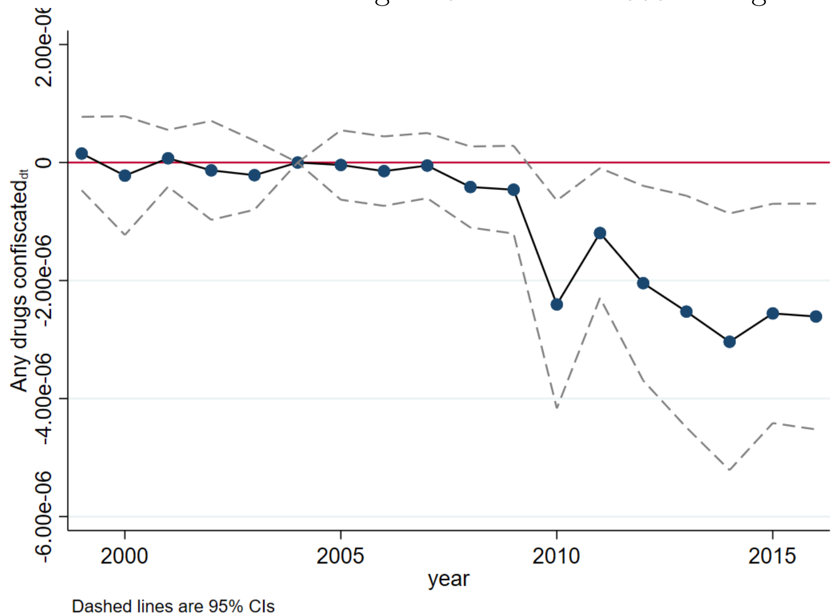
Notes: The figure on the left shows the distribution across Spanish provinces of confiscations of marijuana between 2011 and 2016 originating from Morocco; the figure on the right shows the distribution across Spanish provinces of the number of individuals with Moroccan nationality in 2011.

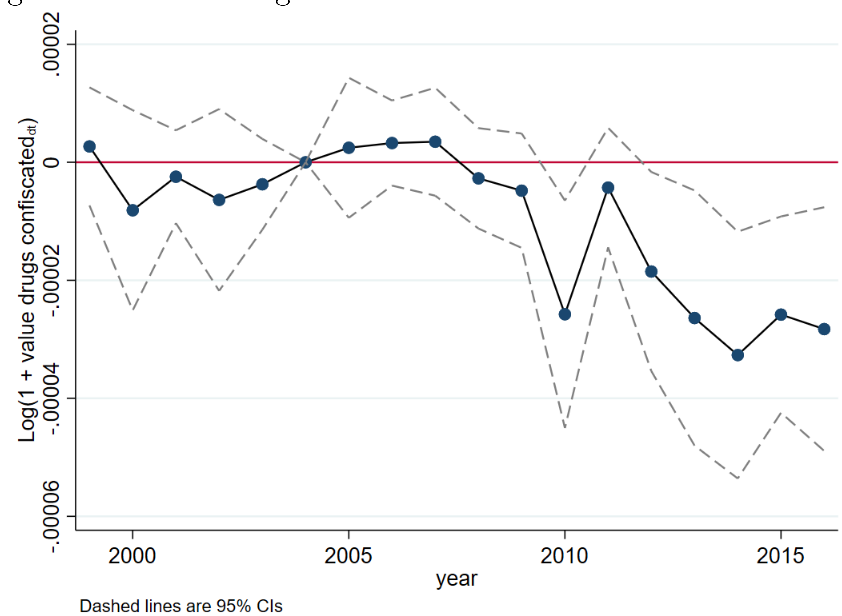
Figure 4: First-Stage Fit



Notes: The figure shows the conditional scatter plots of *Log Migrants* 2011 with the instruments for immigrant inflows in the decade 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 and without outliers.

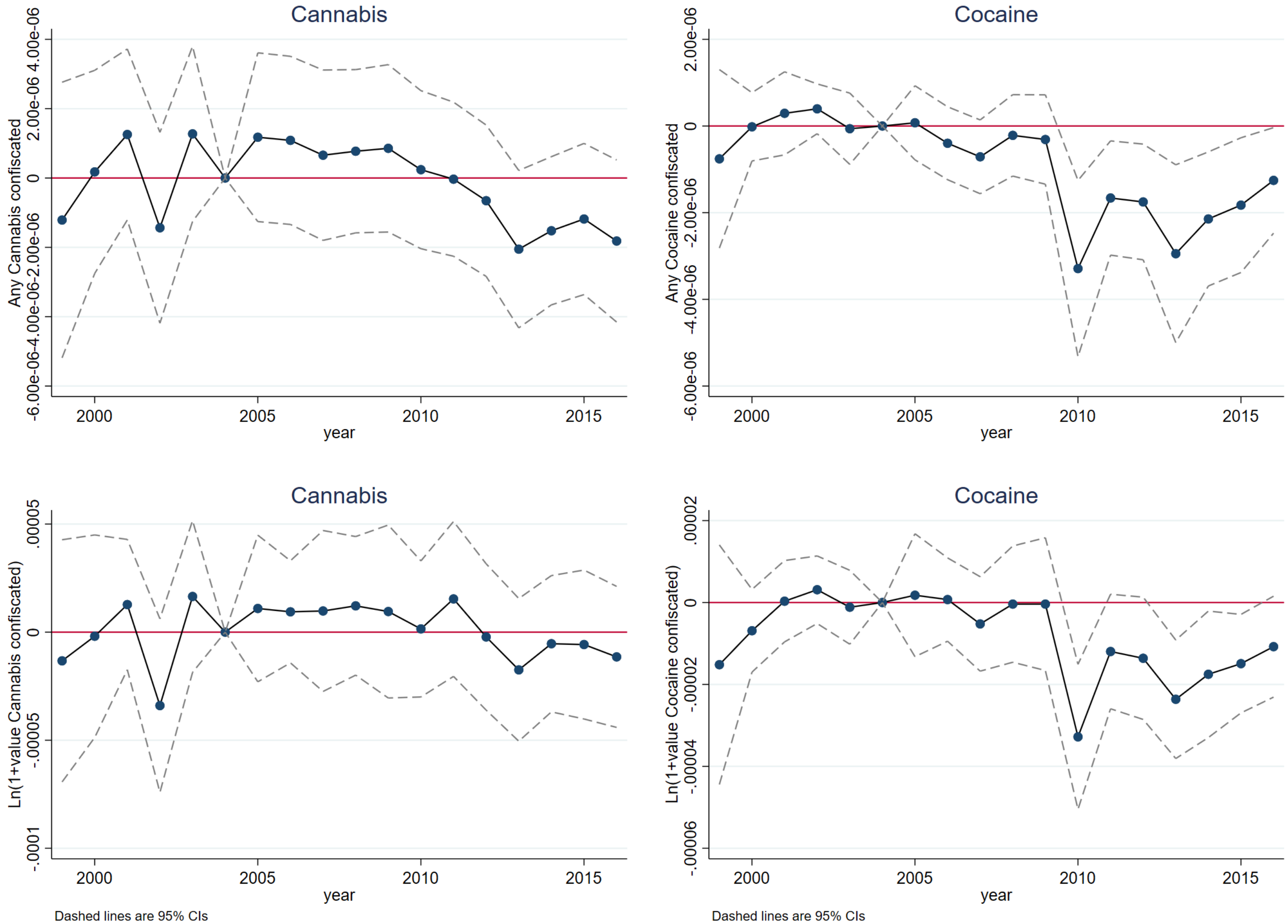
Figure 5: Effect of 2005 Immigrant Regularization on Drug Confiscations





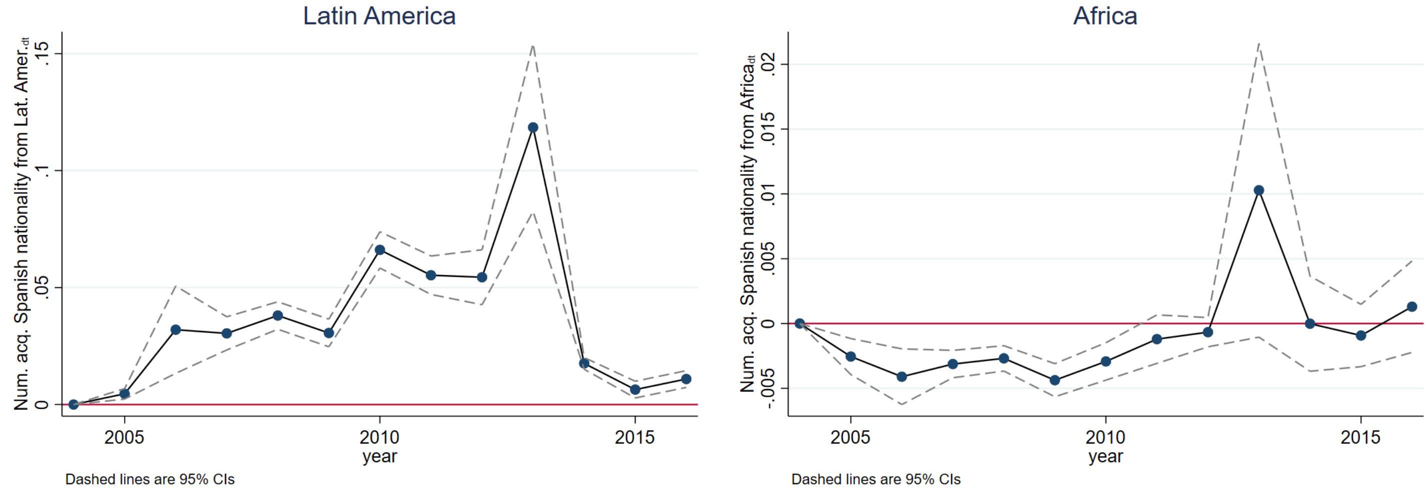
Notes: The figure shows event study plots of the effect of the 2005 immigrant regularization on whether any drugs were confiscated locally (chart on the left) and the log of 1 plus the value of drugs confiscated locally (chart on the right). Plots are estimated using equation 20.

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 drug were confiscated locally in that year, and on the bottom the log of 1 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.

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 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 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, substitute 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

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

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

Consider the case of cocaine, where there is no domestic production, i.e. $T_d = 0$, 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, injuyed 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 Spanish province, t denotes year-month, and $Y_{o,d,t} \in \{\ln(S_{o,d,t,} + 1), \mathbf{1}\{S_{o,d,t} > 0\}\}$. 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.19. I find no statistically significant structural break in confiscations. One caveat for this approach is that if drug traffickers also suddenly change their trafficking behavior and routes to avoid increased enforcement intensity, the same pattern may result.

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 3 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

		Drug Confiscations, 2011-2016			
	(1) First-stage: Log Immigrants 2011	(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*				
	(2.18)				
Predicted immigration, 1991-2001	0.154***				
	(4.70)				
Log Immigrants 2011		0.105**	2.322***	0.0801*	1.276*
		(2.92)	(4.35)	(2.07)	(2.36)
Kleibergen-Paap F-stat.	12.3	12.3	12.3	12.3	12.3
PANEL B: CLUSTERED BY COUNTRY					
Predicted immigration, 2001-2011	0.0374				
	(1.83)				
Predicted immigration, 1991-2001	0.154***				
	(4.66)				
Log Immigrants 2011		0.105	2.322*	0.0801	1.276*
		(1.62)	(2.45)	(1.91)	(2.00)
Kleibergen-Paap F-stat.	11.5	11.5	11.5	11.5	11.5
PANEL C: CLUSTERED BY PROVINCE (BASELINE)					
Predicted immigration, 2001-2011	0.0374*				
	(2.66)				
Predicted immigration, 1991-2001	0.154***				
	(5.92)				
Log Immigrants 2011		0.105**	2.322***	0.0801***	1.276***
		(2.76)	(4.23)	(3.80)	(3.78)
Kleibergen-Paap F-stat.	23.4	23.4	23.4	23.4	23.4

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

	(1) First-stage: Log Immigrants	Import Drug Confiscations 2011-2016 (2) OLS: dummy	(3) OLS: log value	(4) 2SLS: dummy	(5) 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 FEs)

		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 FEs)

		Re-Export Drug Confiscations 2011-2016			
	(1) First-stage: Log Immigrants	(2) OLS: dummy	(3) OLS: log value	(4) 2SLS: dummy	(5) 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 FEs)

	(1) First-stage: Log Immigrants	Re-Export Drug Confiscations 2011-2016 (2) OLS: dummy	(3) OLS: log value	(4) 2SLS: dummy	(5) 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

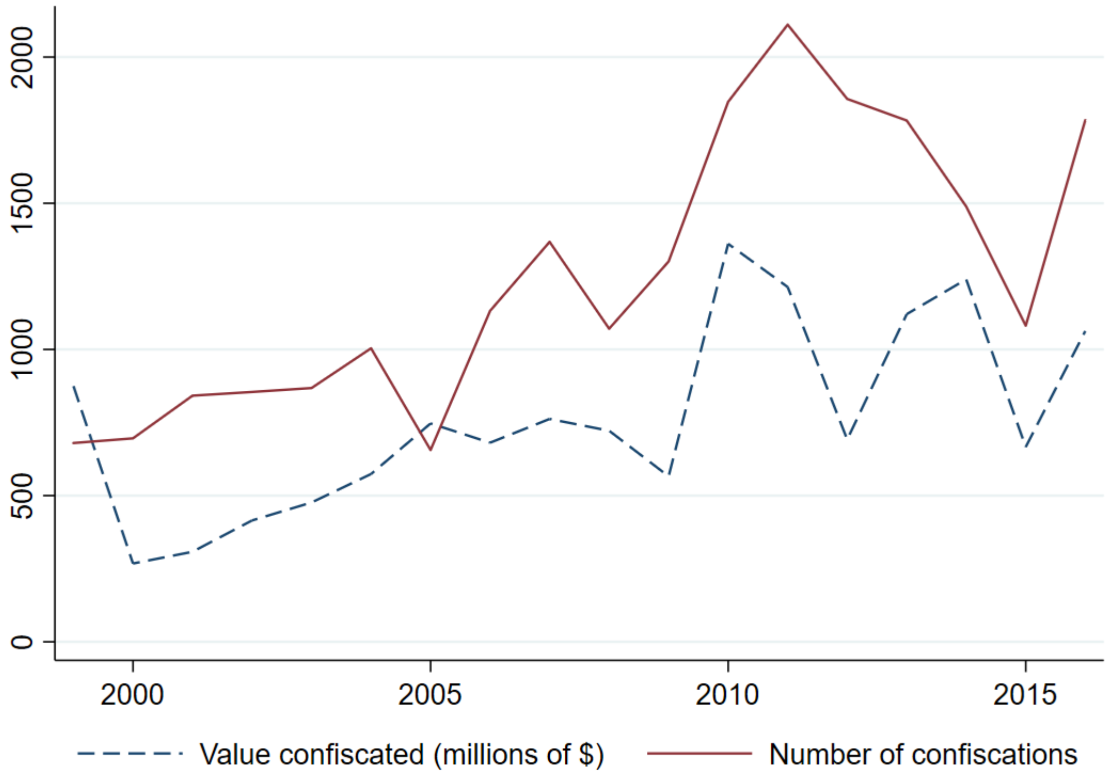
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	(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

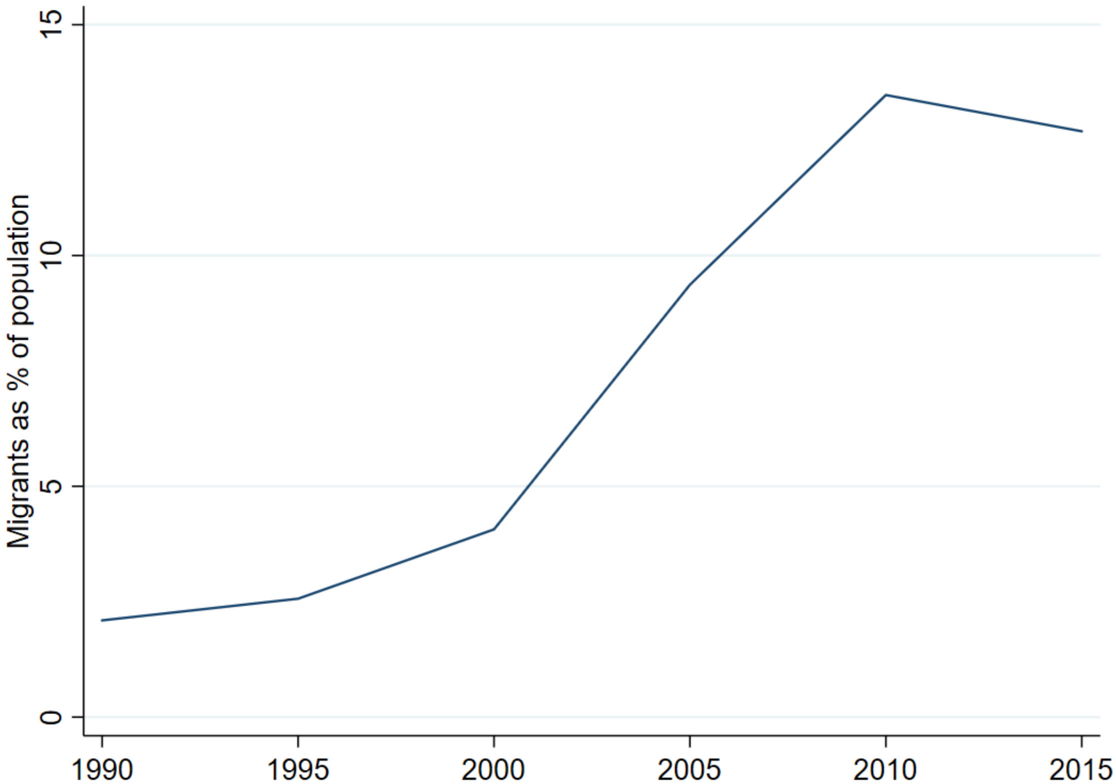
Notes: The table presents coefficient estimates from IV regressions of equation (10) at the province-year level. I instrument for *Log Immigrants* using excluded instrument $IV_{d,t} = \ln\left[\sum_o \left(\frac{Immigrants_{o,d,1981}}{Immigrants_{o,1981}}\right) \times Immigrants_{o,-d,t}\right]$, with 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.1: Illegal Drug Confiscations per Year, 1999-2016



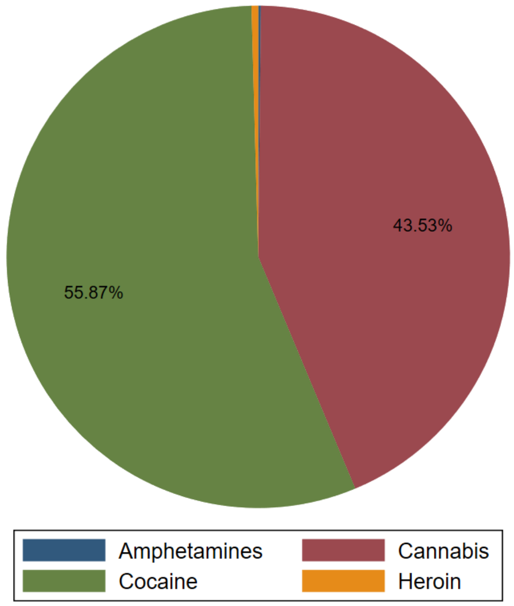
Notes: This figure shows the value of drugs trafficked from foreign countries confiscated over time by Spanish authorities and the number of confiscation events as reported to the UNODC. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure A.2: Immigrant Population Share in Spain, 1990-2015



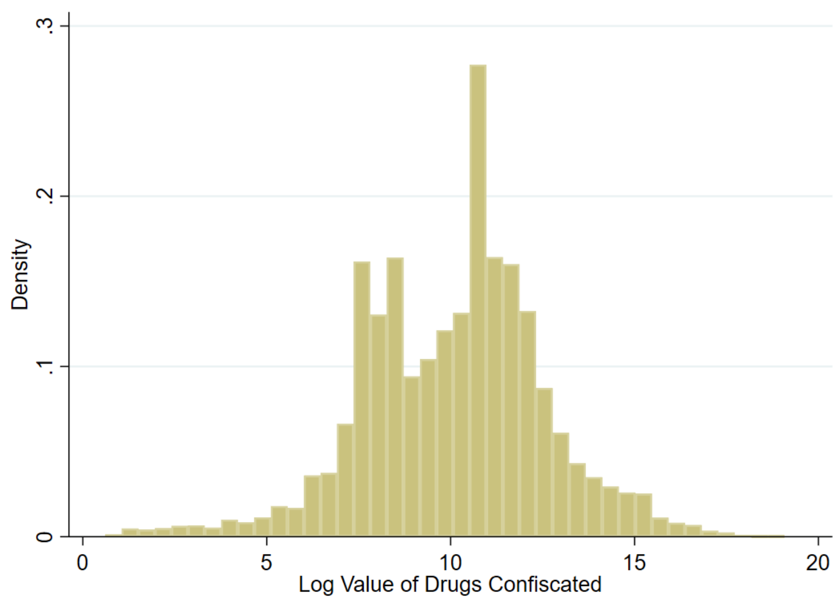
Notes: This figure shows the fraction of the Spanish population born in another country over time. The data are reported by the World Bank but originally come from the United Nations Population Division.

Figure A.3: Confiscations by Drug Type



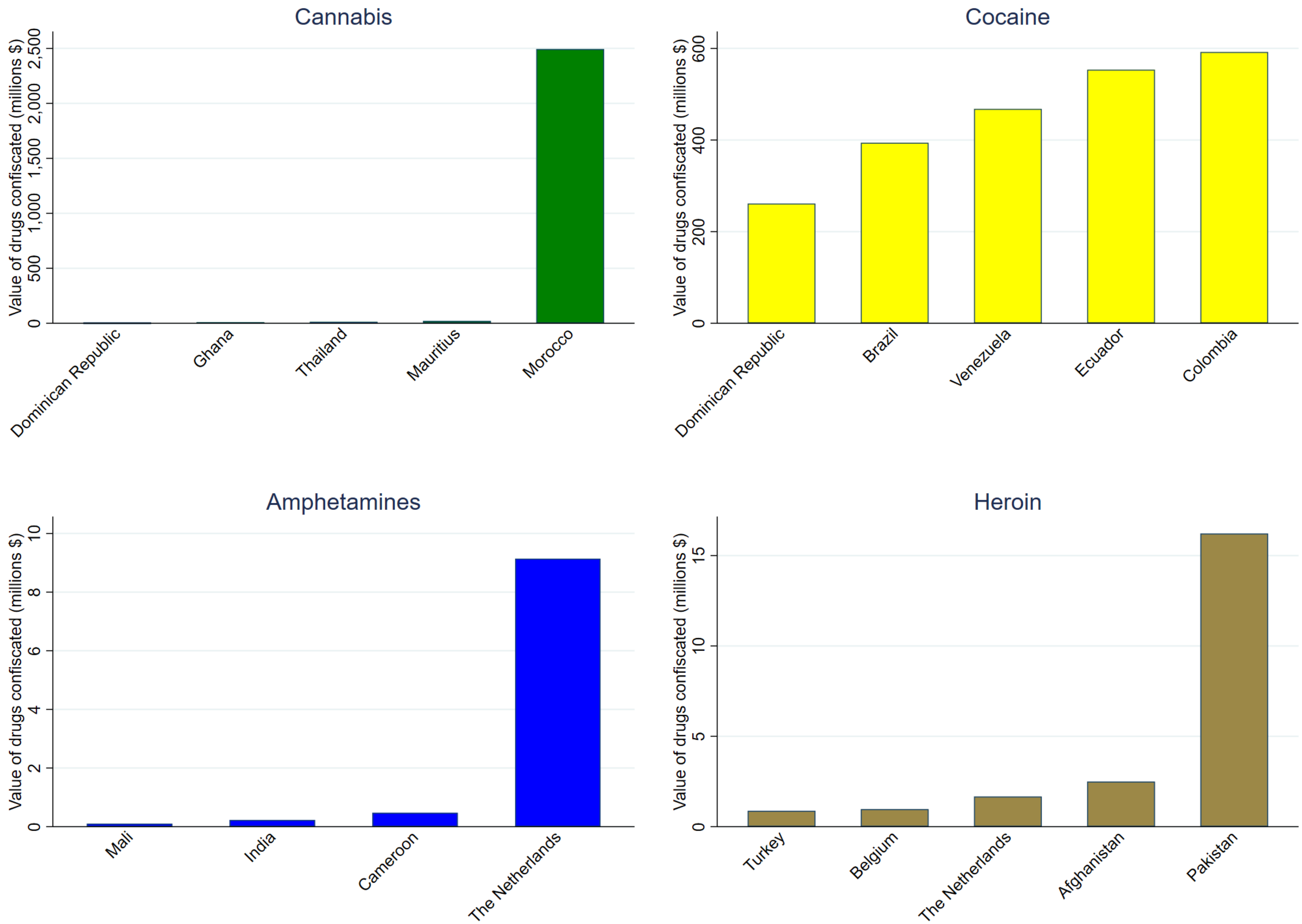
Notes: This figure shows the makeup of drug confiscations in Spain by drug type. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure A.4: Distribution of Log Value of Confiscations



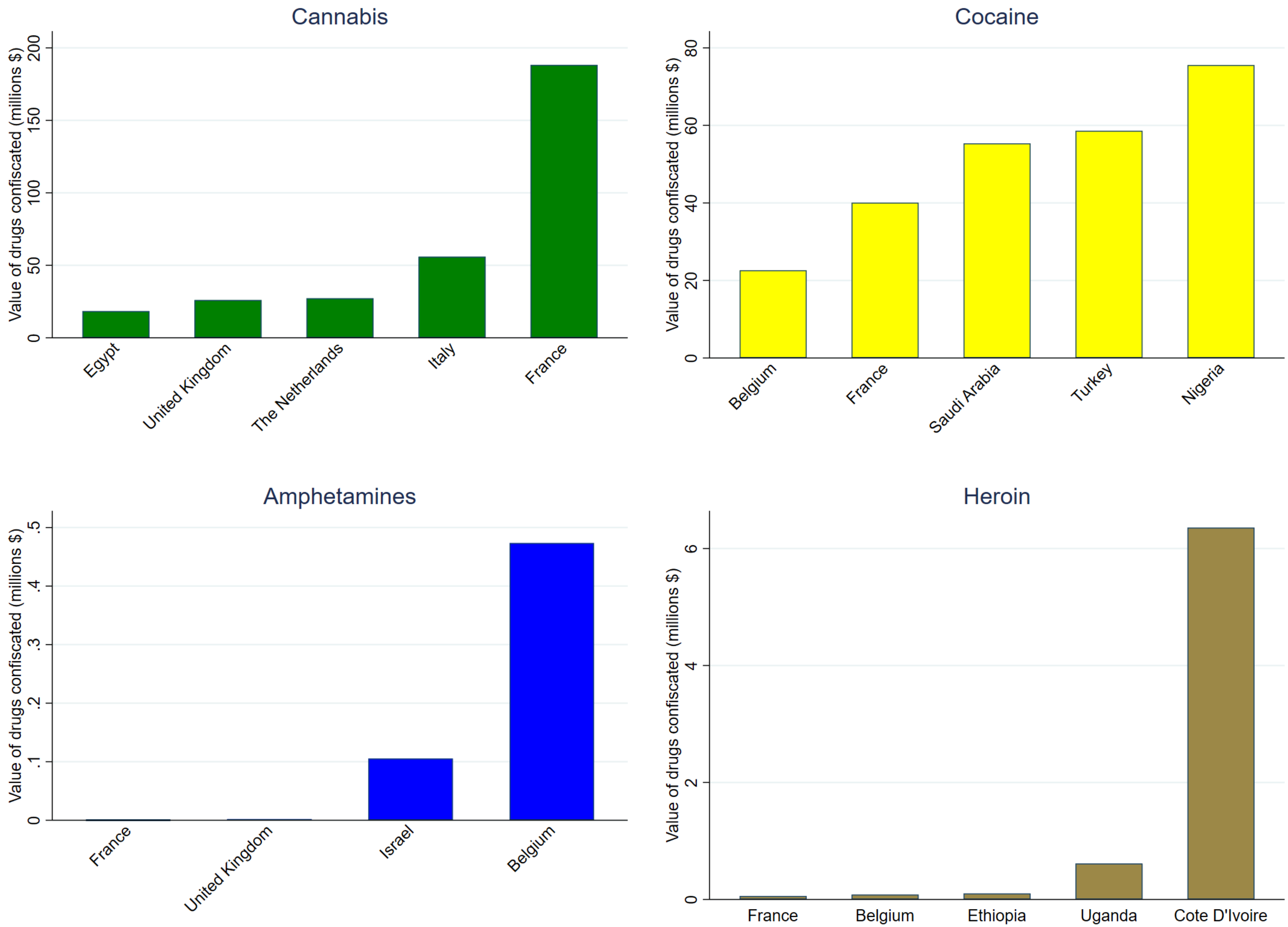
Notes: This figure shows the distribution of the log value of drug confiscations in Spain between 2011 and 2016 as reported to the UNODC. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure A.5: Top 5 Origins by Drug



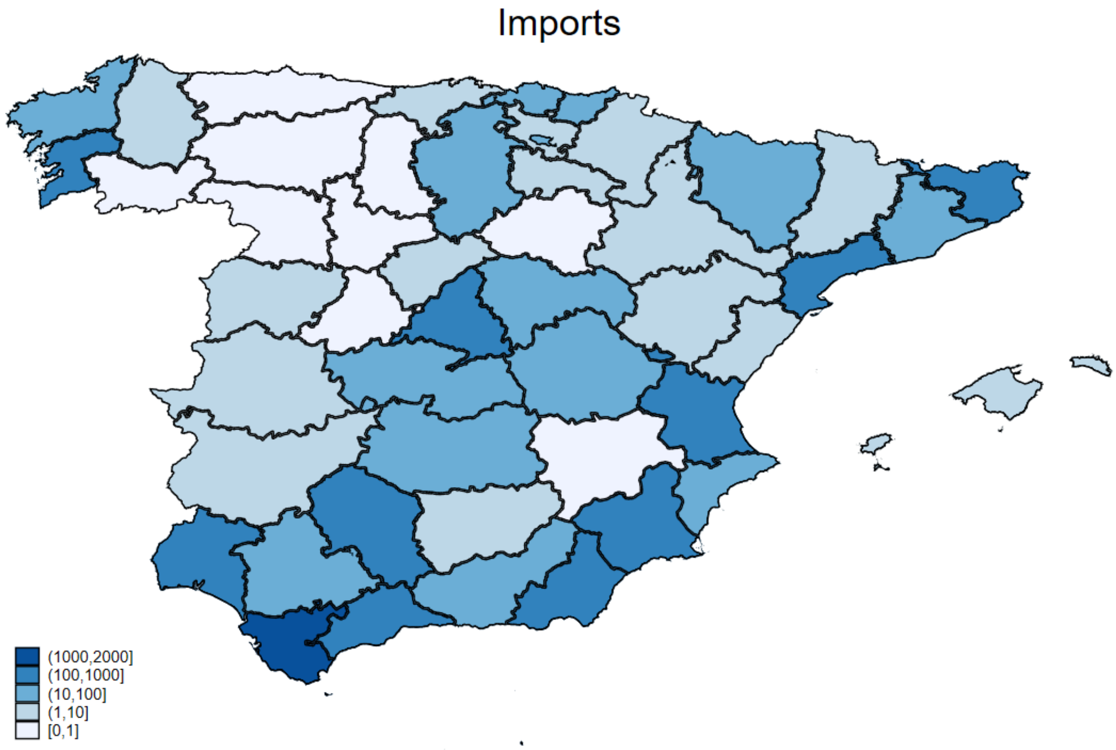
Notes: This figures shows the top 5 exporters of illegal drugs to Spain during 2011 through 2016 by drug as proxied by confiscations by Spanish law enforcement reported to the United Nations Office of Drugs and Crime.

Figure A.6: Top 5 Intended Destinations by Drug



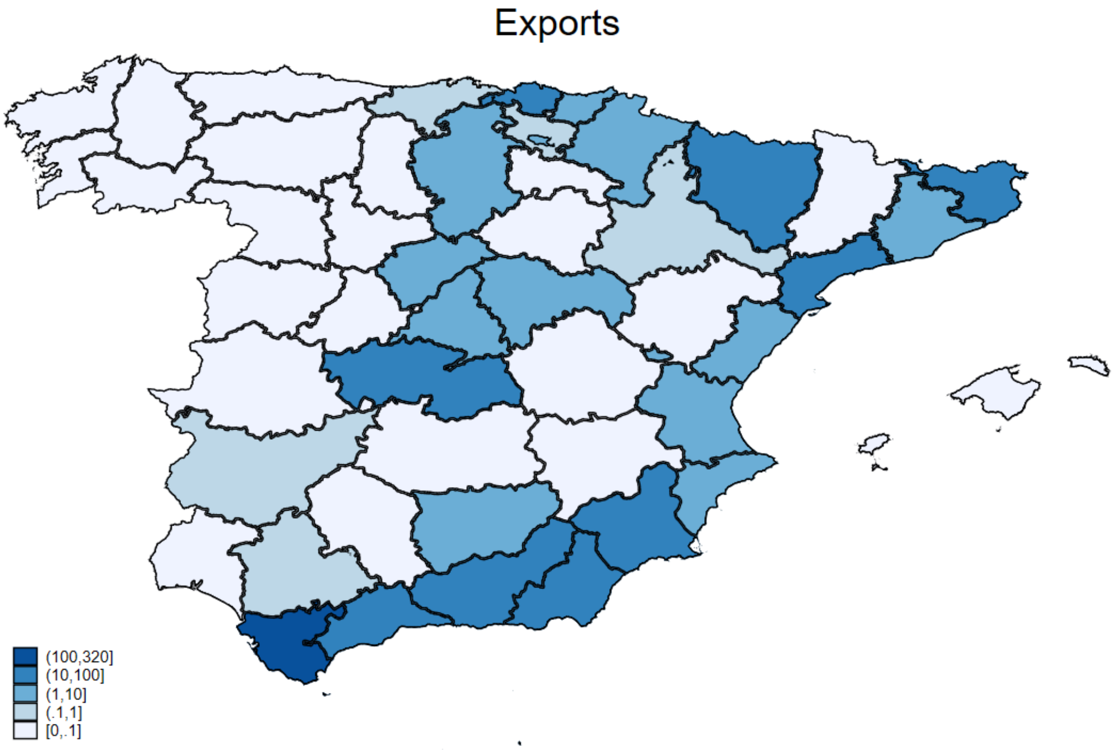
Notes: This figures shows the top 5 importers of illegal drugs from Spain during 2011 through 2016 by drug as proxied by confiscations by Spanish law enforcement reported to the United Nations Office of Drugs and Crime.

Figure A.7: Geography of Drug Import Confiscations in Spain



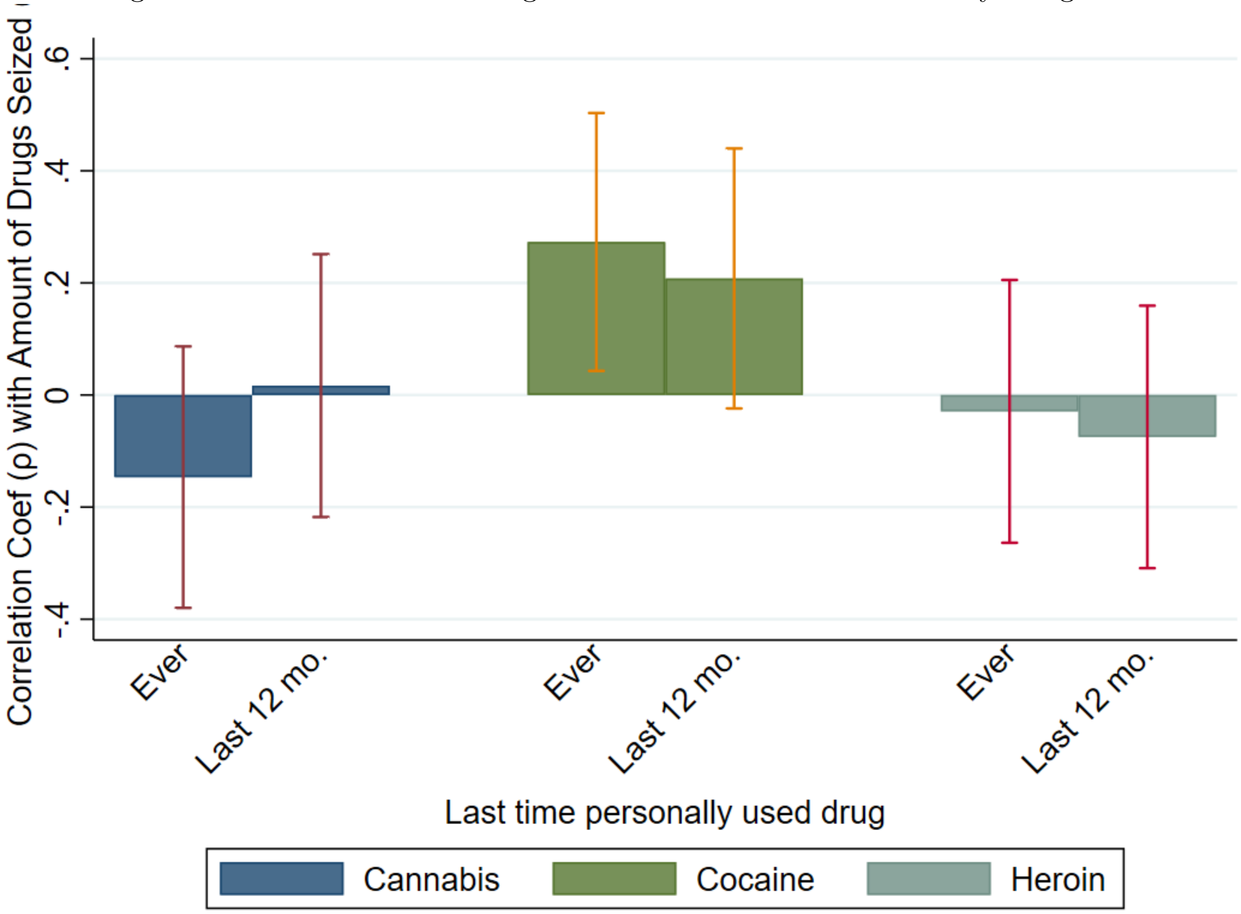
Notes: This figure shows the distribution of drug confiscations of imports (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office of Drugs and Crime.

Figure A.8: Geography of Drug Confiscations Intended for Re-Exports in Spain



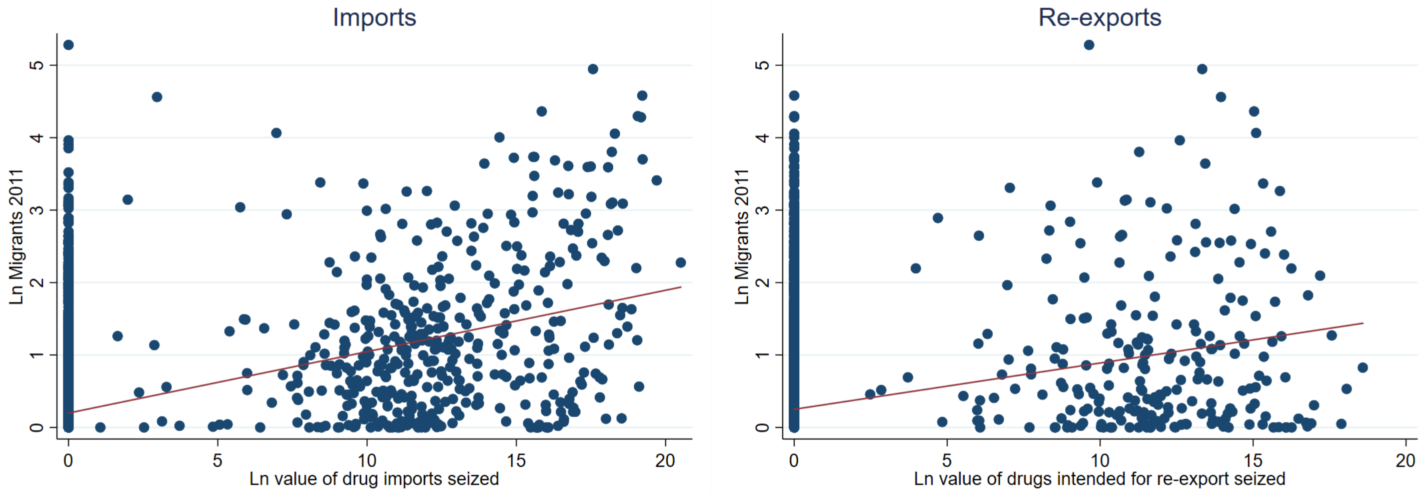
Notes: This figure shows the distribution of confiscations of drugs intended for re-export (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office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

Figure A.9: Correlation of Drug Confiscations to Personal Use by Drug



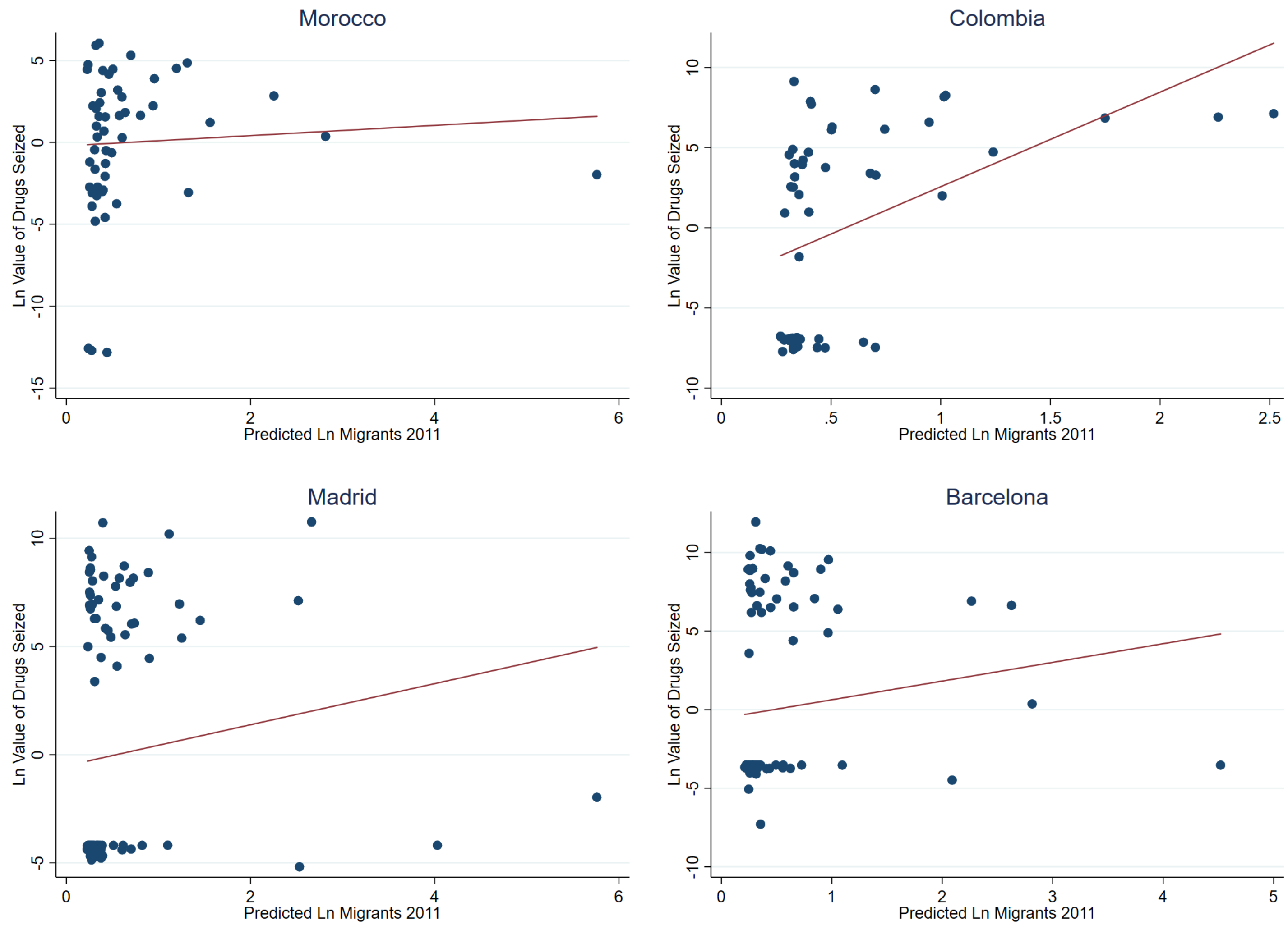
Notes: This figure shows the correlation coefficient between the amount confiscated per capita of a particular drug with the fraction of respondents in a province who report having ever used the drug or having used the drug within the last 12 months averaged over the 2011, 2013, and 2015 waves of the EDADES survey. Amphetamines were not asked about until the 2013 survey, so I exclude them. 90% confidence intervals are shown in red. The sample is a cross-section of 52 Spanish provinces.

Figure A.10: Drug Confiscations and Number of immigrants Raw Correlation



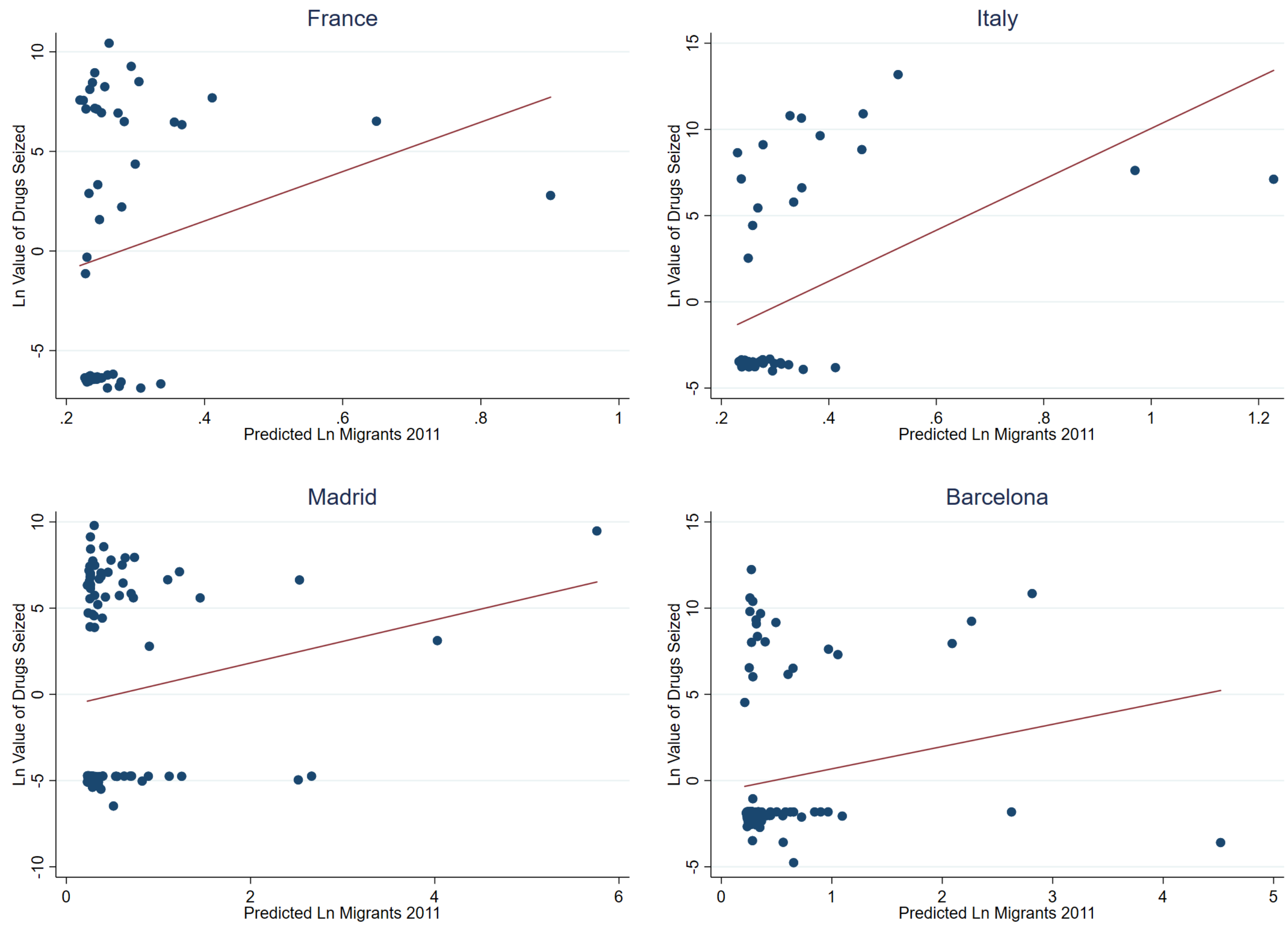
Notes: The figure on the left shows the unconditional scatter plot of the bilateral log value of drug imports confiscated on the x-axis with the bilateral log number of immigrants measured in 2011 on the y-axis. The figure on the same but using the log value of drugs confiscated intended for re-export.

Figure A.11: Migrants and Drug Trafficking Imports



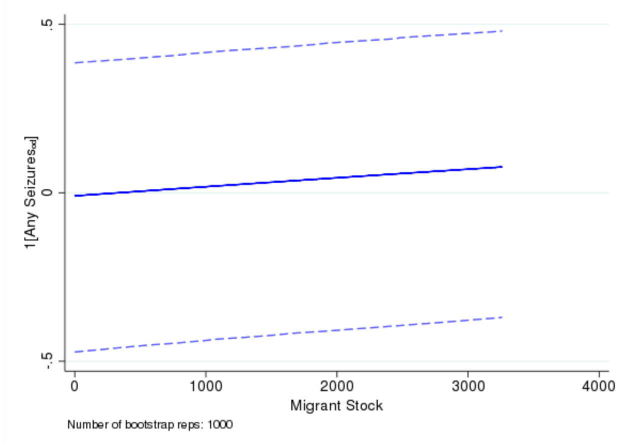
Notes: The figure shows the conditional scatter plots of predicted *Log Migrants* 2011 with the log value of imported drugs confiscated for origins Morocco and Colombia and separately for provinces Madrid and Barcelona. Data are conditional on origin and destination fixed effects and log distance.

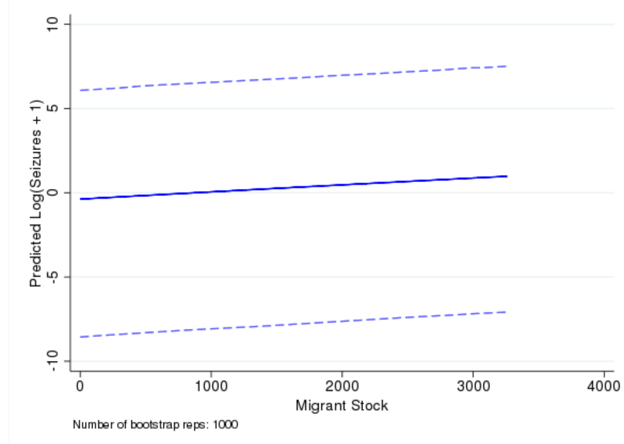
Figure A.12: Migrants and Drug Trafficking Exports



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.

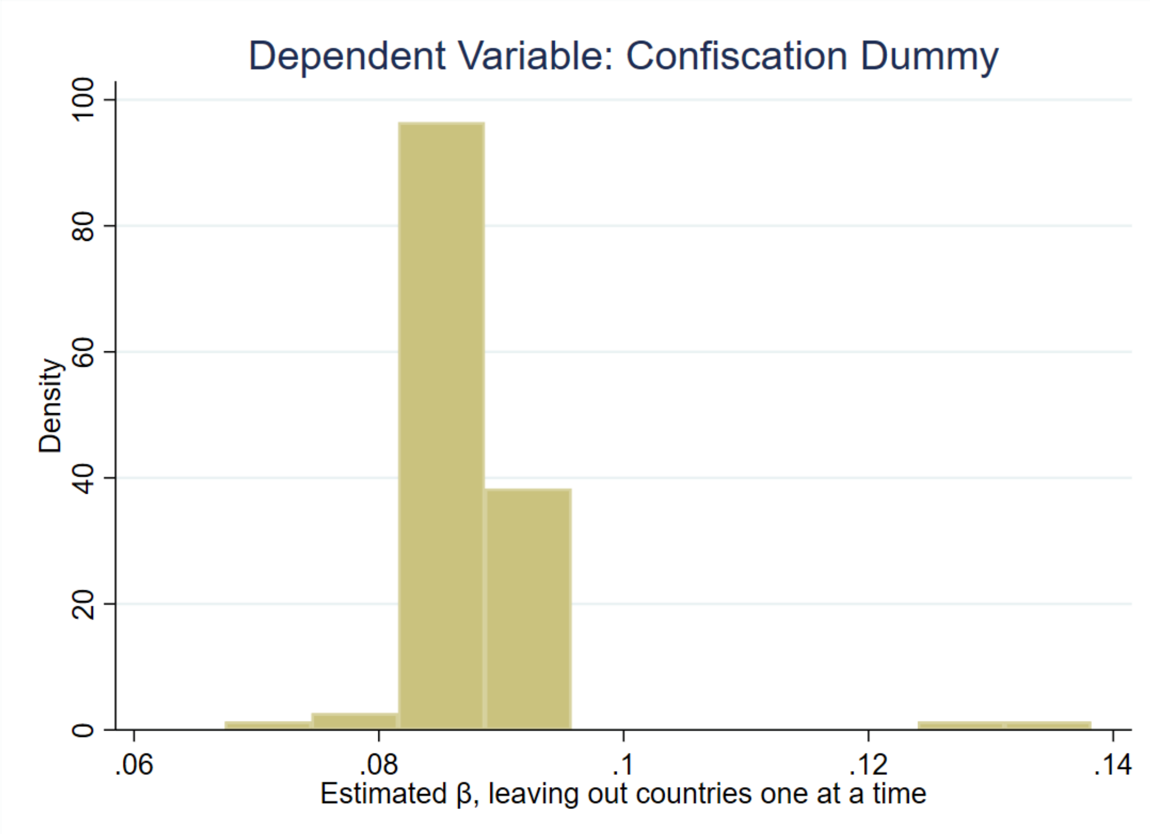
Figure A.13: Non-Parametric Relationship Between Import Drug Confiscations and Bilateral Immigrant Population

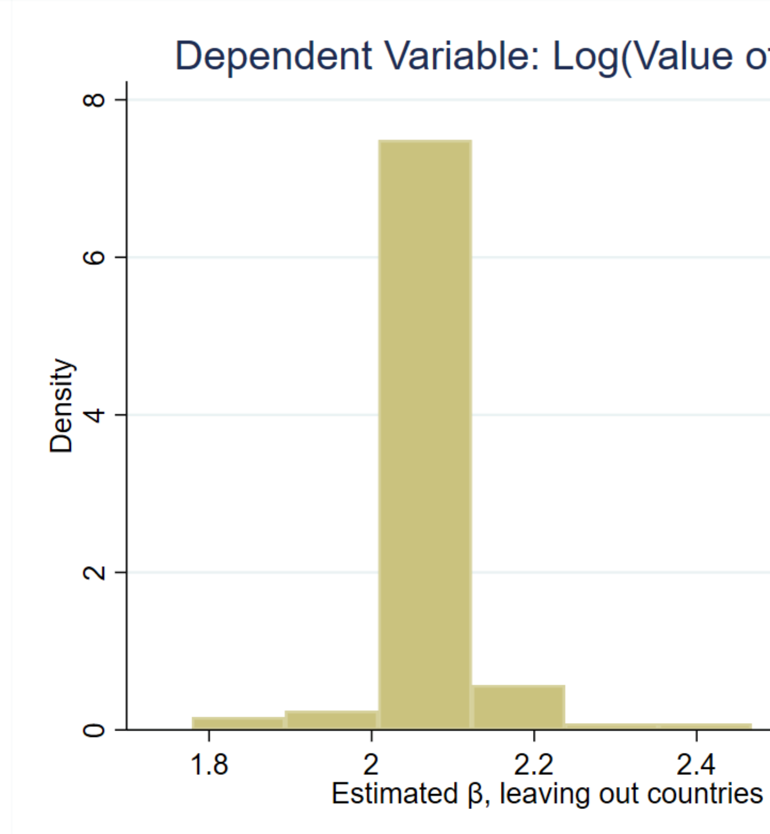




Notes: This figure shows the values of the dummy variable $\mathbf{1}\{S_{od} > 0\}$ (left) or $\log(S_{od} + 1)$ (right) predicted from the non-parametrically estimated function $g(M_{o,d})$, as in $f(S_{o,d}) = \alpha_o + \alpha_d + g(M_{o,d}) + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d}$. S_{od} is 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).

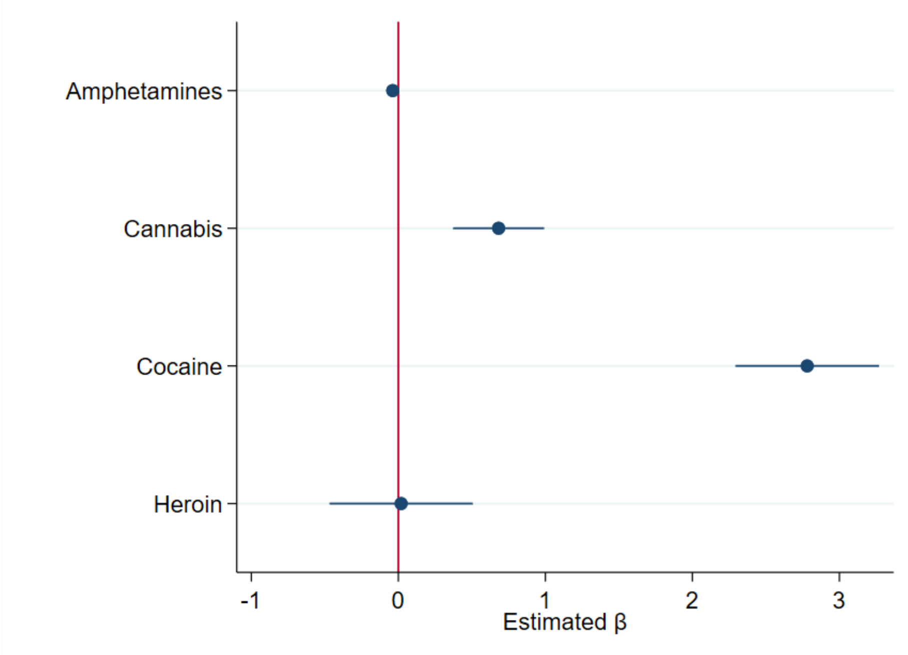
Figure A.14: Effect of Immigrants on Drug Trafficking: Dropping Origin Countries





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 β's when the depdendent 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 1 plus the value of drugs imported from a given origin country and confiscated locally between 2011 and 2016.

Figure A.15: 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 4 drugs included for the baseline estimation. As shown in Figure A.3, cannabis and cocaine make up the vast majority of illegal drugs confiscated by authorities in Spain.

Figure A.16: Binscatter, Any Confiscation on Bilateral Immigrant Population

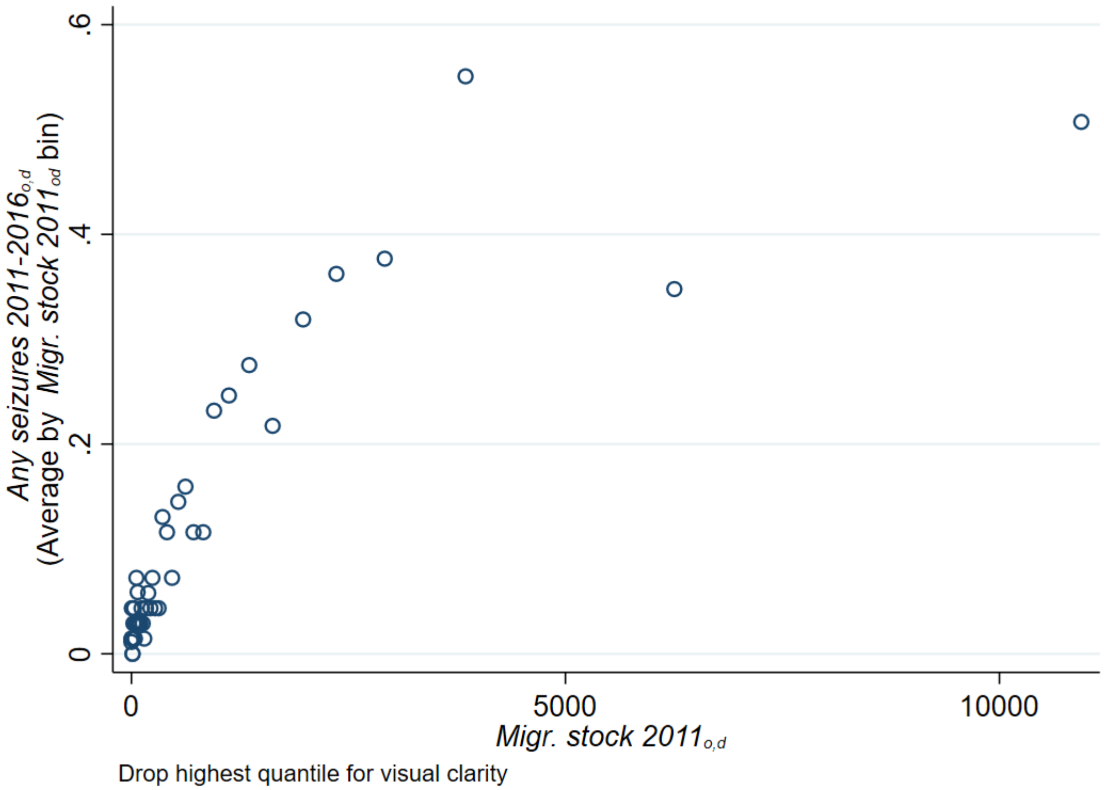
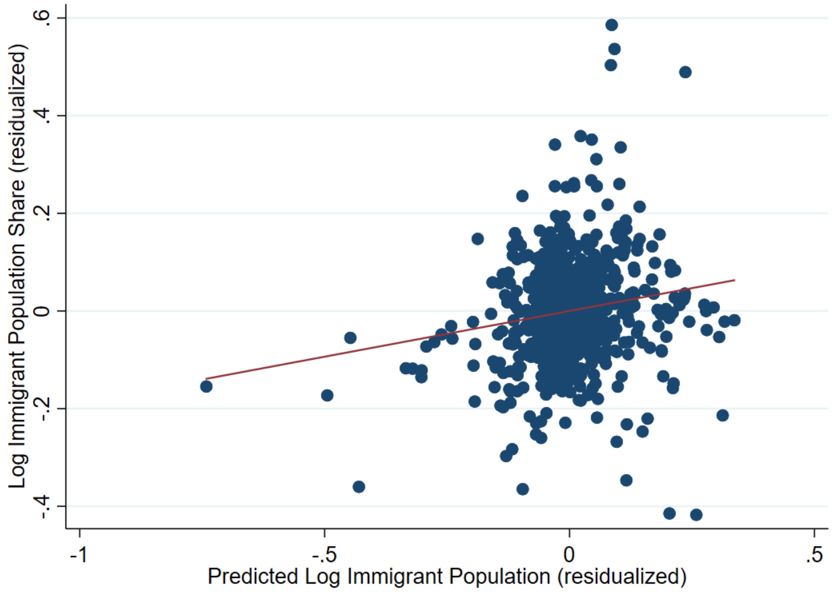
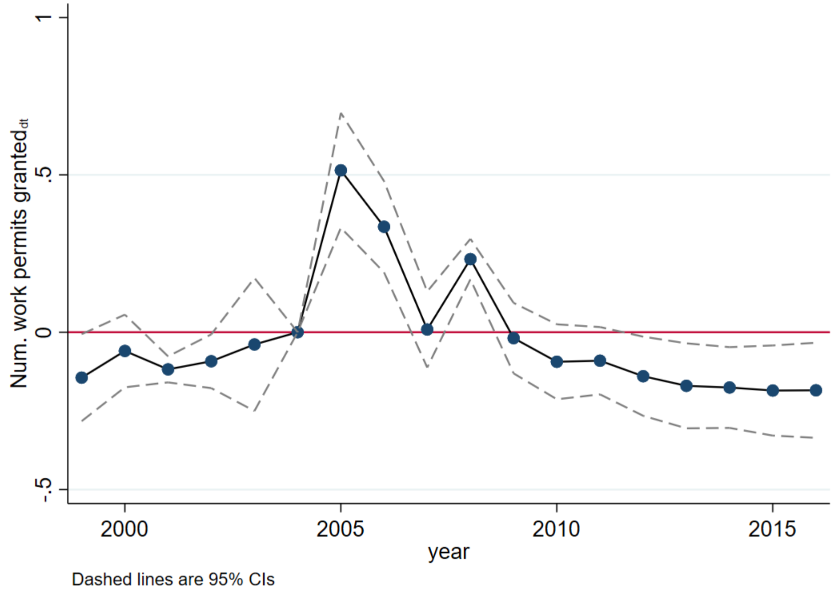


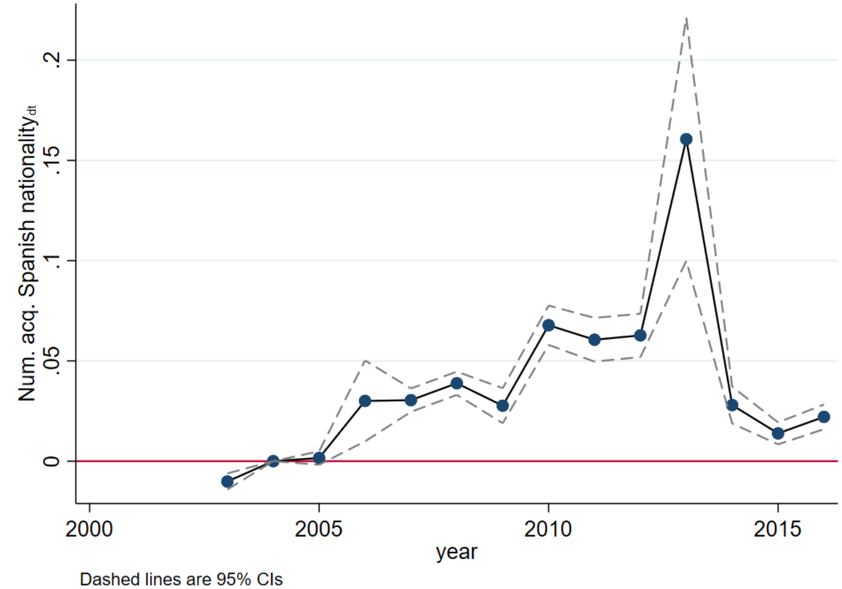
Figure A.17: First-Stage Fit, Province-level Panel



Note: The figure shows the first-stage fit of province immigrant population on the province-level shift-share instrumental variable defined in equation 11, both residualized on year and province fixed effects.

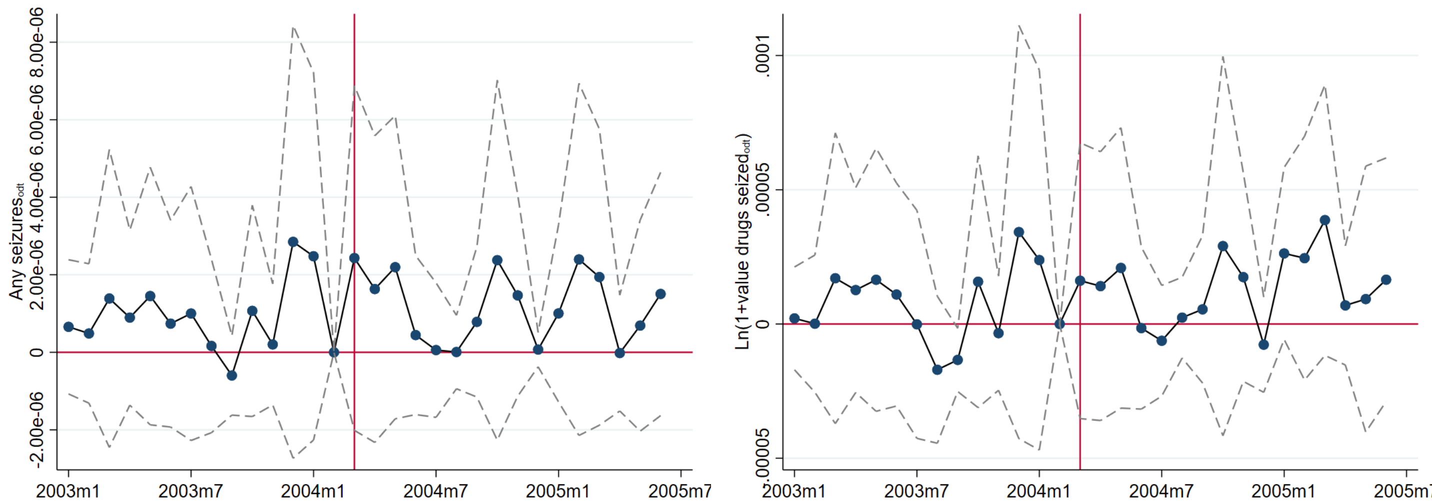
Figure A.18: Effect of 2005 Immigrant Regularization on Work Permits, Naturalizations





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.

Figure A.19: 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.