# Immigrants, Legal Status, and Illegal Trade

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**Abstract**

Nearly $2 trillion of illegally trafficked goods flow across international borders every year, generating violence and other social costs along the way. Some have controversially linked illegal trafficking to immigrants, especially immigrants without legal status. In this paper, I use novel data on nearly 10,000 confiscations of illegal drugs in Spain to study how immigrants and immigration policy affect the pattern and scale of illegal drug trafficking. To identify the causal effect of immigrants on trafficking, I construct an instrumental variable that interacts variation in total immigrant inflows into Spain across origin countries with the fraction of immigrants inflowing into each province. I find that immigrants increase both illegal drugs imported from and exported to their origin country, with irregular immigrants raising illegal drug imports. To better understand the role of legal status, I also exploit an extraordinary regularization of nearly half a million immigrants in 2005. Event study estimates suggest that granting immigrants legal status results in a decline in drug imports.
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# 1 Introduction

Many illegal goods are not produced where they are consumed, resulting in the trafficking of nearly \$2 trillion of illegal goods—worth 10% of the value of legal global merchandise trade—across international borders annually (Mavrellis, 2017). Violence often follows in the wake of illegal trafficking, and further costs to society accrue 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 legally binding contracts (Marsh et al., 2012).

One controversial but untested opinion holds that immigrants, particularly those without legal status, facilitate the trafficking of illegal goods from their origin country to their host region.[1] Immigrants' social connections to their origin country may make arranging for imports and exports easier—be they legal or illegal (Peri and Requena-Silvente, 2010; Combes et al., 2005; Head and Ries, 1998). Moreover, immigrants without legal status are prevented from working in the formal sector, thereby reducing their earnings relative to their legal counterparts (Monras et al., 2021; Kaushal, 2006; Kossoudji and Cobb-Clark, 2002). The Becker-Ehrlich model of crime (Becker, 1968; Ehrlich, 1973) suggests that the differential in earnings resulting from legal status will result in a higher propensity to participate in financially motivated illegal activities, such as trafficking illegal goods.

In this paper, I estimate how immigrants and immigration policy affect the trafficking of one of the most consequential illegal goods: illicit drugs. I use novel data on drug confiscations from Spain and exogenous variation in immigrant populations to show that immigrants have a large, positive causal effect on the import and export of illegal drugs from and to immigrants' countries of origin. I find that immigrants' legal status is a crucial determinant of drug trafficking, with irregular immigrants raising illegal imports and regular immigrants raising illegal exports. I estimate these results using two primary empirical strategies: in my baseline estimation, a conventional gravity equation of illegal trade; and to assess the role of legal status, an event study of a major immigrant regularization program in Spain.

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 the mechanisms that

[1] 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 (Pinotti, 2017). In addition, several notable politicians have made this claim. Donald Trump suggested in 2015 that Mexican immigrants were "bringing drugs [and] crime" into the United States. Then-presidential candidate Sebastian Piñera in 2017 blamed Chile's immigration laws for "importing problems like delinquency, drug trafficking and organized crime" (Esposito and Iturrieta, 2017). In addition, the European Union High Representative for Common Foreign and Security Policy argued in 2003 that, "massive flow[s] of drugs and migrants are coming to Europe and [will] affect its security. These threats are significant by themselves, but it is their combination that constitutes a radical challenge to our security" (Solana, 2003).

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

To make progress on measuring illegal drug trafficking, I use detailed data on drug confiscations that include information on which country the drugs were trafficked from. In particular, I use a database of individual drug confiscation events 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 each drug confiscation occurred within Spain, from which country the drugs were trafficked, and 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.

The context of Spain provides unique advantages for studying whether and how immigrants and immigrant legal status affect the flow of illegal drugs. First, Spain is a major hub for cocaine and cannabis trafficked into the European market. Second, the country has also experienced elevated immigration in recent decades, much of it unauthorized. Third, I exploit institutional features in Spain that facilitate the measurement of irregular immigrant populations. Unlike the United States and many other European countries, immigrants to Spain can obtain healthcare and other government benefits regardless of their legal status in exchange for enrolling in their local population registry. Comparing local population registries with counts of permits for legal residency leads to a straightforward imputation of the size of the irregular immigrant population (González-Enríquez, 2009; Gálvez Iniesta, 2020).

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

The rich set of fixed effects afforded by the gravity equation allow me to control for unobserved heterogeneity that may potentially bias my estimates, including unobserved variation in policing enforcement. As in many studies of the economics of illegal behavior (Pinotti, 2020), I rely on official records based on enforcement actions carried out by police to proxy for true illegal activity. However, the rich variation across origins and destinations in the gravity model allows me to control for policing enforcement intensity at both the immigrants' nationality and province level, which is not typically feasible in studies about the role of immigrants in crime. In particular, the country fixed effects absorb variation in law enforcement activity directed towards specific nationalities in Spain (for example, if Spanish police uniformly discriminate against Moroccans) while the province fixed effect absorbs variation in law enforcement efficacy in confiscating drugs across provinces (for example, if Barcelonan police are especially skilled at confiscating drugs).

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

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

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

I also find that general equilibrium responses, including changes in the participation of the native-born in drug markets, cannot fully explain the estimated relationship between immigrants and trafficking. I assess the strength of these general equilibrium responses in two ways. First, I chart the path of confiscations over time between high immigration and low immigration provinces. I observe that provinces with an initially large immigrant population experience a substantial increase in confiscations, while low immigration provinces experienced relatively flat confiscations. These trends suggest that the rise in confiscations were not offset by declines in confiscations elsewhere. Second, I estimate the effect of immigrants on drug market activity at the province level. I find that an increase in the immigrant population in a province (across all origin countries) raises the value of drugs confiscated locally. Both exercises point to immigrants raising total illegal drug imports.

I find two mechanisms drive my results. First, immigrants' social connections to their origin country—e.g., family, friends, or professional contacts—reduce the search costs for arranging for import and export transactions. My quantitative evidence is consistent with the extant qualitative evidence that immigrants reduce information frictions and transaction costs for illegal imports and exports.

Second, I find that immigrant legal status crucially impacts the effect that immigrants have on illegal trafficking. To understand the role of legal status, I estimate the effect of immigrants on drug trafficking separately by immigrant legal status using the gravity specification. I find that my baseline estimates for imports are driven primarily by irregular immigrants, consistent with the Becker-Ehrlich model of crime. However, regular immigrants drive the estimated baseline effect for exports to the immigrants' origin country. The effect of regular immigrants on exports results from the fact that Spain's primary export destinations for illegal drugs are countries within the European Union, where all E.U. immigrants to Spain have de facto regular status. Moreover, in contrast to illegal imports, illegal exports are often conducted by wholesale distribution companies whose fleet of trucks can transports both legal and illegal goods. The individuals running trafficking operations within these firms are typically owners or managers of the firm, and thus must be citizens or immigrants with legal status.

To better understand the effect of legal status on trafficking, I exploit a major immigrant regularization program implemented in 2005. This program resulted in roughly half a million immigrants receiving legal status (Monras et al., 2021).I find that the 2005 mass immigrant regularization reduced the likelihood of illegal drug importation significantly. For example, I estimate that legalizing 10% of the irregular immigrant population from a given origin country would reduce the likelihood of illegal drug imports from that country by 1.4 percentage points. I find no effect of the regularization program on illegal drug exports.

This paper provides the first causally identified estimates of the effect of immigrants and immigrant legal status on illegal trafficking. While economists have not studied how immigrants affect transnational flows of illegal goods, related work by criminologists Berlusconi et al. (2017), Giommoni et al. (2017), and Aziani et al. (2019) use country-pair level data on drug confiscations to assess how immigrant populations at the country-pair level correlate with drug confiscations. I make four main advancements relative to this literature. First, I use credibly exogenous variation in bilateral immigrant population. Second, I include origin and destination fixed effects to control for observed and unobserved factors at the region-level that shape immigration and trafficking. Third, I exploit within-country variation, which allows me to control country-pair level factors. Finally, I explore the underlying mechanisms that drive the observed immigrant-trafficking relationship and the resulting immigration policy implications.

This article contributes to the debate on the costs and benefits of immigration and on which immigration policies host countries should adopt. Much of the literature on the consequences of immigration has focused on labor market outcomes.[2] A separate literature has estimated the effect of immigrants on legal trade (Burchardi et al., 2019; Parsons and Vézina, 2018; Cohen et al., 2017; Peri and Requena-Silvente, 2010; Combes et al., 2005; Rauch and Trindade, 2002; Head and Ries, 1998; Gould, 1994). This paper expands upon this literature by looking at how a new outcome—illegal trade—changes as a result of immigration, and by showing that the legal status regime of the host country is crucial for shaping this relationship.

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

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

[2]See, for example, Monras (2020), Dustmann et al. (2013), Ottaviano and Peri (2012), Borjas (2003), and Card (2001). For a recent review of the literature, see Dustmann et al. (2016).

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

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

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

# 2 Background and Measurement of Drug Trafficking

## 2.1 Background

**Illegal Drugs.** The most commonly consumed illegal drugs around the world are cannabis, opioids, amphetamines and prescription stimulants, ecstasy, and cocaine, ranked by number of users in 2018 (p.7, UNODC, 2020b). Spain is a key entry point for much of the cocaine and cannabis entering the European illegal drug market.[4]

Illegal drugs typically pass through many countries between the production location and the 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 typically passes through intermediary countries such as Mexico or West Africa on the way to these markets (p. 30, UNODC, 2020a).

Cannabis, by contrast, "is produced in almost all countries worldwide." (p. 67, UNODC, 2020a) Nevertheless, a large amount of cannabis is still trafficked across international borders, although it tends to remain in the same region (p. 71-73, UNODC, 2020a).

In Spain, confiscations of domestic cannabis plants (Alvarez et al., 2016) are quite small compared to the amount of cannabis confiscated arriving from abroad. Amphetamines can also be produced locally, but are a small part of the market, with only 2% of drug treatment patients seeking help for an amphetamine addiction. This fraction is roughly in line with the share of amphetamines in total confiscations observed in the UNODC data.[5]

2017) and violence (Castillo et al., 2020). A notable exception is Dell (2015), who estimates how crackdowns shape violence and drug trafficking networks. However, Dell (2015) lacks data on the bilateral flows of illegal drugs.

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

[5]For the distribution of drug treatment patients by drug, see https://www.emcdda.europa.eu/countries/drug-reports/2019/spain_en. For the distribution of confiscations by drug in the UNODC data, see Figure D.1.

Due to the intermediary-intensive nature of trafficking, social connections between countries may facilitate trafficking routes. In a set of interviews in the United Kingdom conducted by Matrix Knowledge Group (2007), jailed traffickers shared the importance of social ties. Employees in the drug trafficking sector are typically recruited through employers' existing social networks[6], and traffickers also noted examples in which a shared nationality raised trust between individuals seeking to conduct illegal trade transactions.[7] Proximity to immigrants from a variety of drug source countries was seen as advantageous as it reduced search costs.[8] 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 are particularly salient in the case of illegal transactions.

**Immigration.** Spain has experienced tremendous amount of immigration in recent decades. Between 1991 and 2011, the share of immigrants in Spain's population rose from below 1% to well over 10% as shown in Figure D.3, representing "the highest rate of growth of the foreign-born population over a short period observed in any OECD country since the Second World War" (OECD, 2010).

Immigrants without legal status, or irregular immigrants, are a common feature of immigration in Spain. Irregular immigrants are defined as those living in the country without a residency permit, and they usually enter Spain through legal means (González-Enríquez, 2009). These include immigrants who overstay their tourist visas and stay in Spain beyond the terms of their temporary residence permits.[9] Moreover, irregular immigration is a common phenomenon in Spain. Surveys of immigrants in Spain have found high rates of immigrant irregularity (Pajares, 2004; Yruela and Rinken 2005). Díez Nicolás and Ramírez Lafita (2001) found that 83% of immigrants had arrived in Spain in the late 1990s and early 2000s without a work permit but nevertheless began to work or look for a job.

Concurrent with its high levels of immigrant irregularity has been Spain's relatively more generous provision of public services to irregular immigrants as well as providing a path to regular status and thereafter to citizenship. For example, the country has regularly

[6]"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)

[7]For example, "[One 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)

[8]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)

[9]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).

provided legal status to hundreds of thousands of irregular immigrants in successive waves of regularization 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 enroll in the local population registry. These benefits create a strong incentive for irregular immigrants to register, a fact that I leverage to measure irregular migrant prevalence in Section 5.1.

## 2.2 Drug Trafficking Data Description

Data limitations typically complicate the study of illegal activity. In this study, 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 drugs, I compare confiscations to survey-based measures of drug availability at the province level.

I use a database of nearly 10,000 individual drug confiscation events to proxy for actual drug flows in the context of Spain, a country with high-quality reporting of drug confiscations.[10] 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.[11] Similarly, Dube et al. (2016) uses the number of opium poppy and cannabis plants eradicated as a proxy for cultivation.

I measure drug confiscations using a novel dataset of individual wholesale-level confiscations events compiled by the United Nations Office of Drugs and Crime (UNODC). The UNODC data cover the universe of reported drug confiscations, regardless of the nationality of the perpetrator. An observation in these data is a single drug confiscation event which details the drug type, the amount confiscated, the country from which the drugs were trafficked, the country to which the drugs were intended to be trafficked (which could be Spain), 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. 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.[12]

I focus on Spain due to the high quality of their reported confiscations data.[13] Three national law enforcement agencies—the National Police, the Guardia Civil, and the Customs and Excise Department—submit data to a centralized federal database. The three agencies

[10] I discuss these data in greater detail in Appendix Section A.1.

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

[12] Specifically, these are prices in dollars for 2012 for heroin, cocaine, amphetamines, and cannabis as reported by Spain to the UNODC.

[13] For more on the UNODC drug confiscations data, see Appendix Section A.1.

report confiscations both made by their own personnel and 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 are assigned based on subsequent investigation, where country of origin refers to the most recent foreign country the drugs had been in (not necessarily the country in which they were produced). For some drug interdictions, assignment of origin and destination country is fairly straightforward. For drugs confiscated from airline passengers upon arrival at an airport, the most common mode of transport of confiscated drugs as shown in Figure D.2, the origin country is the passenger's departure country and destination country is the passenger's ultimate destination on their travel itinerary. For less straightforward cases, such as the case of drug gangs transporting cocaine intercepted in the Atlantic Ocean off the Galician coast, the country of origin and destination is determined based on additional information such as suspect and witness interviews and coordination with law enforcement agencies in the suspected origin and destination countries. If a person is arrested within Spain for drug trafficking but is outside an airport or port, the country of origin of the drugs will be determined on the basis of the investigation carried out, including any statements made by the arrested person.[14]

Four facts emerge when looking at the data on confiscations in Spain. First, nearly all drugs confiscated by Spanish authorities are cocaine or cannabis, with negligible amounts of amphetamines and heroin as shown in Figure D.1. Second, the distribution of drug confiscation amounts is right skewed as shown in Figure D.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 D.5, and Spain exports drugs primarily to the rest of Europe and the Mediterranean region, as seen in Figure D.6. Finally, there is substantial spatial variation across Spain of the import and export of illegal drugs, as shown in Figures D.7 and D.8.

## 2.3 Validation Exercise

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

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

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

I find that confiscations of illegal drugs positively correlate with a wide range of measures of local drug availability. In Figure 1, I plot the correlation coefficient between reported ease or difficulty obtaining a particular drug within 24 hours and the amount of that drug that was confiscated in the province per capita between 2011 and 2016.[15] Consistent with confiscations corresponding to real flows of illicit drugs, I find that when a higher proportion of respondents say it is "impossible" to obtain a particular drug, the amount of that drug confiscated in the province tends to be lower. Conversely, I find that the proportion of respondents saying it is "easy" or "very easy" to obtain a drug correlates positively with the amount of that drug confiscated in the province. This relationship is much stronger for cannabis and cocaine, the major drugs imported into Spain, and weaker for heroin, whose pathway into Europe is believed to lie through the Balkan countries rather than through Spain (UNODC, 2014).

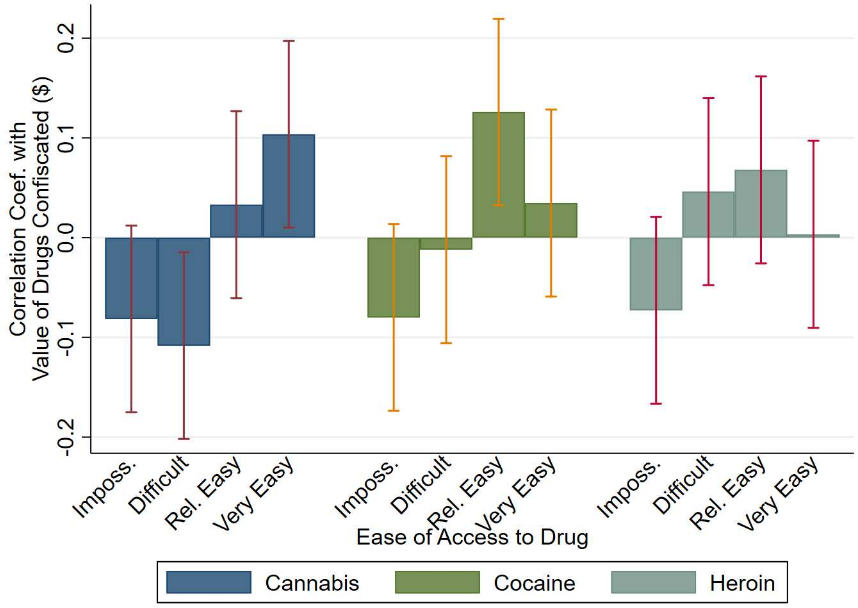
In Figure 2 I plot the correlation coefficients of additional measures of local drug availability and use to the value of confiscations per capita across all illicit drugs. In the first bar of the figure, the local drug availability measure is the fraction of respondents to the question, "Thinking about where you live, how important of a problem do you think illegal drugs are?" who answer, "Very." For the remainder of the bars, the drug availability measures are the fraction of respondents who report seeing various drug behaviors exhibited by others in their neighborhood.[16] For each survey question, confiscations either vary positively with local drug availability or have a correlation statistically near zero.

I also find that confiscations are weakly correlated with respondents' personal drug use history, as shown in Appendix Figure D.9. I find a positive correlation between confiscations and personal use for cocaine, with imprecise zeros for cannabis and heroin. Overall, these results suggest that confiscations by law enforcement are a valid proxy for actual flows of illicit drugs.

[15] 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 within 24 hours.

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

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




*Notes*: This figure shows Pearson correlation coefficients between the amount of confiscations per capita of a particular drug with the fraction of respondents in a province who report finding it impossible/difficult/relatively easy/very easy to obtain that drug within 24 hours. Amphetamines were not asked about until the 2013 survey, and are thus excluded. Ninety percent confidence intervals are shown. Correlations are estimated on a cross-section of 52 Spanish provinces, averaged across 2011 to 2016 for drug confiscations and across the 2011, 2013, and 2015 waves of the EDADES (Survey on Alcohol and Drugs in Spain).

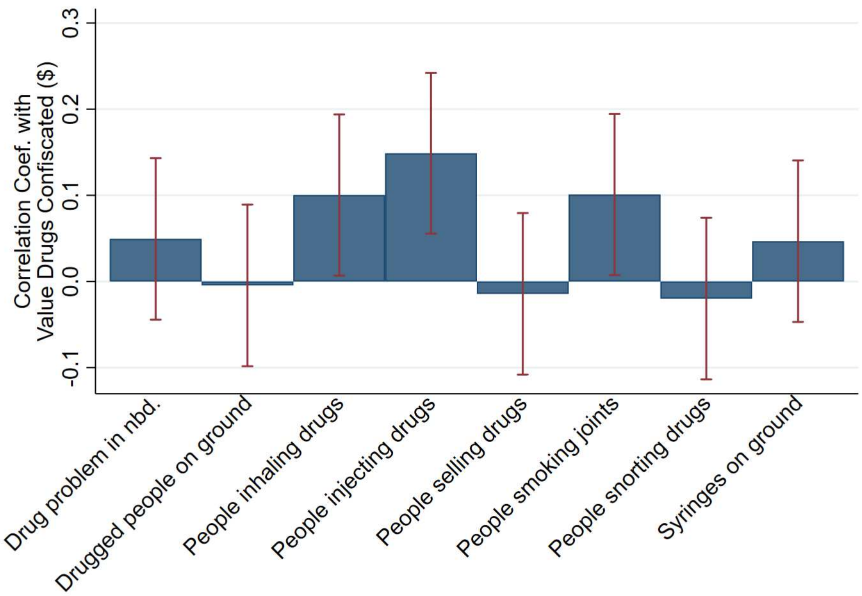
# 3 Bilateral Empirical Analysis

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

## 3.1 Preliminary Evidence

There exists a positive unconditional correlation between the number of immigrants and the value of drugs confiscated at the country-province level, as shown in Appendix Figure D.10.

Figure 2: Correlation of Drug Confiscations to Measures of Local Drug Availability

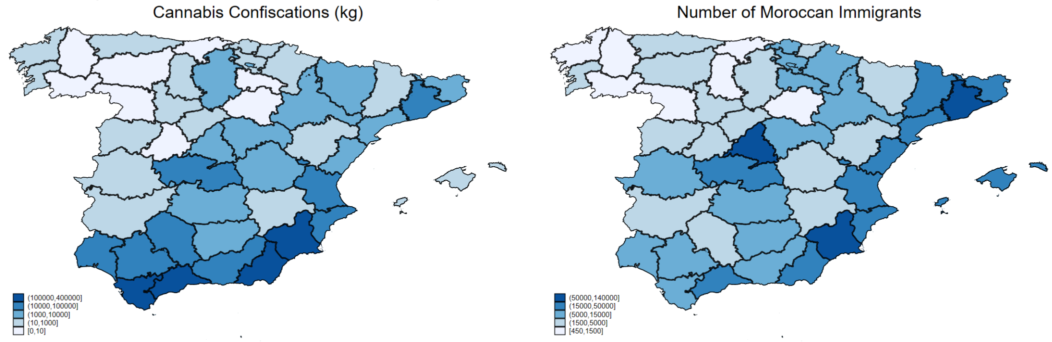



*Notes*: This figure plots Pearson correlation coefficients between illegal drug confiscations (measured in dollars) per capita across all drugs and the fraction of respondents in the province who reported observing the listed drug-related behaviors either "frequently" or "very frequently" or, for the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

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

A natural explanation for this correlation is that geographic distance—since Morocco is directly to the south of Spain—drives both trafficking and immigration from Morocco and

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




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

into southern Spain. Other confounders, such as the similar climate enjoyed by parts of Spain and Morocco may also explain this correlation. To more formally evaluate the relationship between immigrants and drug trafficking and rule out such confounders, I next estimate a gravity equation of drug confiscations in the context of Spain.

## 3.2 Gravity Regression

The two-dimensional nature of my data and the gravity equation allows me to flexibly control for origin- and destination-specific characteristics that may shape trafficking and migration. This estimation strategy also allows me to deal with concerns about enforcement intensity variation driving observed drug confiscations.

I estimate a baseline gravity equation of the form

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

where $\alpha_o$ and $\alpha_d$ are country and province fixed effects, respectively; $Y_{o,d}$ is either a dummy for whether any drug imports from $o$ into $d$ were confiscated between 2011 and 2016 or a dummy for whether any export from province $d$ to country $o$ were confiscated between 2011 and 2016; and $Dist_{o,d}$ is the distance in kilometers between $o$ and $d$ taken from Peri and Requena-Silvente (2010). $M_{o,d}^{2011}$ is a measure of the number of immigrants from $o$ living in $d$, defined as the log of one plus the number of immigrants in $d$ from $o$, measured in thousands (my results are robust to alternative functional form choices, as I show in Appendix Section C.1). The error term $\varepsilon_{o,d}$ includes all omitted bilateral forces that may shape drug trafficking. I measure the immigrant population $M_{o,d}^{2011}$ using the 2011 Spanish Census distributed by the Minnesota Population Center (2019).[17]

The origin country and destination province fixed effects are key to my identification strategy. The origin fixed effect $\alpha_o$ controls for, among other factors, the economic development, institutions, and crime in the origin country as well as national-level policies of Spain vis-a-vis origin country $o$. These country-pair level policies can include visa regimes, customs regulations, and national law enforcement priorities. Similarly, the province fixed effect $\alpha_d$ controls for province $d$ factors common across origins, such as province $d$'s police force strength and the economic conditions in $d$. For example, if the labor market in Barcelona attracts immigrants and raises the demand for cocaine, $\alpha_d$ will absorb such variation to the extent that it is constant across origin countries. Thus $\beta$ is identified from variation in drug confiscations and immigrant populations across country-province pairs.

I cluster standard errors at the origin country-level in my baseline specification, though my results are robust to alternative standard error choices (see Appendix Table C.5).

I estimate equation 1 separately for import confiscations and export confiscations. To measure intended exports, I consider drugs confiscated in $d$ but that were intended to go to country $o$.[18]

## 3.3 Instrumental Variables Approach

While country and province fixed effects absorb many potential confounders in my baseline specification, there may still be unobserved factors at the country-province-pair level, such as the geographic or climatic similarity between a foreign country and a Spanish province. Consider, for example, that Morocco shares a similar Mediterranean climate with Barcelona. This similar climate is preferred by Moroccan immigrants, who therefore are more likely to settle in Barcelona. If Moroccan narcotraffickers are more skilled at piloting their narcoboats in the Mediterranean climate, then similar climate may also drive Moroccan drug traffickers to Barcelona. Hence similar climate is a country-province-specific confounder which may drive both immigration and drug trafficking.

To obtain variation in country-to-province-specific immigration that is exogenous to such concerns, I follow Burchardi et al. (2019) and develop a set of leave-out push-pull instruments for the number of immigrants arriving in a given region and coming from a given origin country.[19] These instruments produce plausibly exogenous variation in bilateral immigrant

[17] I provide further detail on the census data construction in Appendix A.2.

[18] In the data, I observe substantially more confiscations on the import margin than I do on the export margin. In particular, the value of import confiscations is nearly 6 times larger than that of export confiscations between 2011 and 2016.

[19] This approach also bears resemblance to Sequeira et al. (2020), who generate exogenous variation in local immigrant populations by interacting the inflows of immigrants to the U.S. (push) and the locations of

inflows. I use two decades of inflows between 1991 and 2011 to predict the current number of immigrants from a given origin country living in a Spanish province.

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

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

$$I\tilde{V}^{D}_{o,d} = I^{D}_{o} \times \frac{I^{D}_{d}}{I^{D}},$$

where $I^{D}_{o}$ is the number of immigrants from origin $o$ coming to Spain in decade $D$, and $I^{D}_{d}/I^{D}$ is the fraction of immigrants to Spain who choose to settle in $d$ in decade $D$.

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

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

To avoid such endogeneity, I again follow Burchardi et al. (2019) and leave out both the continent of origin country $o$ and the autonomous community (the highest-level administra-

new railroads in the U.S. (pull).

tive unit in Spain) of province $d$ to construct the instrumental variable that I use in my baseline estimation:

$$IV_{o,d}^{D} = I_{o,-a(d)}^{D} \times \frac{I_{-c(o),d}^{D}}{I_{-c(o)}^{D}} \tag{2}$$

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

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

The identification assumption is that any confounding factors that make a given province more attractive for both immigration and drug trafficking from a given country do not simultaneously affect the interaction of (i) the settlement of immigrants from other continents with (ii) the total number of immigrants arriving from the same country but settling in a different autonomous community. A violation may occur if, say, immigrants skilled at drug trafficking from Morocco tend to settle in the province of Barcelona and immigrants skilled in drug trafficking from Lebanon settle in Alicante (Barcelona and Alicante are in different autonomous communities) in the same decade and for the same reason: a preference for the familiar Mediterranean climate. Moreover, if Moroccans are a large fraction of immigrants settling in Barcelona and Lebanese immigrants are a large fraction of the immigrants settling in Alicante, then the instrument is predicting bilateral immigration based on a confounding factor: climatic similarity between the immigrants' origin country and the Spanish province. To account for such a correlation across continents and autonomous communities in the reasons for immigrating and trafficking drugs, I also estimate my baseline specification with an alternative instrumental variable set that leaves out countries and provinces with correlated immigration flows, as detailed in Appendix Section C.3.[20]

Finally, to account for spillovers in immigration flows between decades and potential nonlinearities, I also include second-order interaction and squared terms for the instruments, which allow me to better predict the nonlinear immigrant population measure that I use.

[20] I further provide additional discussion of the identification provided by the instrument conditional on the set of country and province fixed effects in Appendix Section B.

Nevertheless, my baseline results are robust to more parsimonious sets of instruments as shown in Appendix Section C.3.

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.[21]

## 3.4 First-Stage

In Figure 4, I plot the residualized first-stage fit of the instruments for the two decades of predicted inflows. All variables are residualized on the set of country and province fixed effects as well as distance. The instruments vary positively with the log number of immigrants, as expected. Moreover, the first-stage strength is driven by variation in the important drug sending and receiving regions: Morocco (the top exporter of cannabis to Spain), Latin America (the top exporter of cocaine to Spain), and Europe (the top recipient of exported Spanish drugs). In Table 1 I show first-stage regressions with different sets of instruments. Instruments from both decades have a positive and statistically significant coefficient across specifications.

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

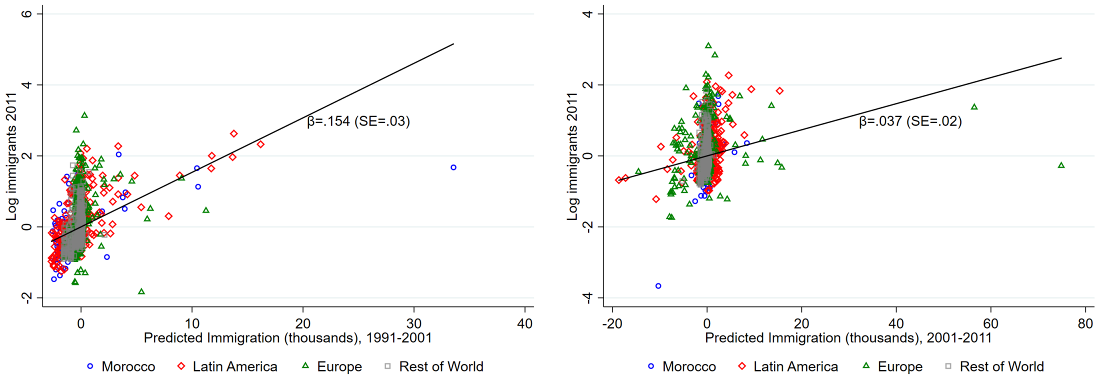
## 3.5 Results

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

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

[21] I discuss the Spanish Census data in greater detail in Appendix Section A.2.

Figure 4: First-Stage Fit




*Notes*: The figure shows the conditional scatter plots of *Log immigrants* 2011 with the instruments for immigrant inflows for decades 1991 to 2001 (on the left) and 2001 to 2011 (on the right). Both *Log immigrants* 2011 and the predicted inflows are residualized on origin and destination fixed effects, log distance, and on the instrument from the left-out decade. Each point represents an immigrant origin country-by-destination Spanish province pair, with immigrant origin regions color coded. For example, immigration from Morocco to the 52 Spanish provinces is plotted with blue circles, while immigration from Latin America is plotted with red diamonds. The regressions depicted correspond to column 3 of Table 1.

from the immigrants' origin country will be confiscated locally by nearly 0.8 percentage points.[22] For comparison, 8.4% of country-province pairs confiscated some amount of illegal drugs being imported into Spain.

In column 2, I find that immigrants also increase exports of illegal drugs. The coefficient estimate is 0.0579 (SE=0.0348). This estimate implies that a 10% increase in the number of immigrants relative to the mean raises the likelihood that drugs will be exported to the immigrants' origin country and confiscated locally by nearly 0.3 percentage points.[23] The point estimate for exports may be smaller than for imports because exports may be more difficult to measure than imports, as police target their efforts on preventing drugs from entering Spain rather than from leaving the country. Nevertheless, the 95% confidence intervals overlap, so I cannot rule out equality between the two coefficients.

There are two biases relative to the OLS to take account of. First, there may be confounding variables at the country-province-pair level which drive both immigration and drug trafficking between locations. These confounders will tend to bias the OLS estimates upwards. Second, the number of immigrants from a given country living in a Spanish province

[22] Using $\hat{\beta} = 0.163$ from column 1 in Table 2, can compute: $\mathbb{1}\left[C^{2011\text{–}2016}_{o,d,Imports} > 0 | M^{2011}_{o,d} = 942\right] = 0.163\left(\ln\left(1 + \frac{942\times 1.1}{1000}\right) - \ln\left(1 + \frac{942}{1000}\right)\right) \approx 0.0077$.

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

Table 1: First Stage Regressions

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

*Notes:* The table presents coefficient estimates from first-stage regressions at the country-province level. All regressions control for province and nationality fixed effects as well as log distance. Standard errors are clustered at the country level. Column 4 corresponds to my baseline estimation set of instruments. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

may be mismeasured, biasing the OLS estimates downwards. My two-stage least squares estimates are statistically indistinguishable from the OLS estimates, suggesting that after controlling for a rich set of fixed effects, bilateral confounders do not substantially bias the OLS estimates.

### 3.6 Robustness of Baseline Estimates

In Appendix C, I show that my baseline results are robust to alternative functional form choices, variations in the set of instruments, and alternative standard error clustering. I also show that my results hold across a wide range of subsamples of the data, as well as in a panel estimation. I also compare my results to the effect that immigrants have on legal trade using the same empirical setup.

Table 2: Effect of Immigrants on Drug Trafficking

| | (1) | (2) |
|---|---|---|
| | Imports | Exports |
| PANEL A: 2SLS | | |
| Log immigrants 2011 | 0.163*** | 0.0579* |
| | (0.0455) | (0.0348) |
| Observations | 5564 | 5564 |
| | Imports | Exports |
| PANEL B: OLS | | |
| Log immigrants 2011 | 0.137*** | 0.0696*** |
| | (0.0221) | (0.0216) |
| Observations | 5564 | 5564 |
| Country FEs | Y | Y |
| Province FEs | Y | Y |
| Log distance | Y | Y |

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

### 3.7 Value of Drugs Confiscated

I next estimate the effect of immigrants on the value of drugs confiscated. In order to measure the value of the dependent variable in logs without dropping zero values, I use pseudo-Poisson maximum likelihood estimation (PPML) (Silva and Tenreyro, 2006). Due to the non-linearity of PPML, I take a control function approach to generating exogenous variation in the immigrant population (Petrin and Train, 2010; Morten and Oliveira, 2018).

In particular, I estimate the first-stage as in column 4 of Table 1 and add the residuals to the PPML estimating equation. The PPML first-order condition is then

$$\sum_{o,d} \left(Value\ confiscated^{2011-2016}_{o,d} - \exp(\delta_o + \delta_d + \beta M^{2011}_{o,d} + \zeta \hat{\epsilon}^M_{o,d} + \gamma \ln(Dist_{o,d})\right) X_{o,d} = 0 \tag{3}$$

where $Value\ confiscated^{2011-2016}_{o,d}$ is the value in dollars of illegal drugs confiscated between country $o$ and province $d$; $\hat{\epsilon}^M_{o,d}$ is the first-stage residual; and $X_{o,d}$ is the vector of variables included in the exponential function (i.e., dummies for countries and provinces, $M^{2011}_{o,d}$, $\hat{\epsilon}^M_{o,d}$, and $\ln(Dist_{o,d})$. I estimate equation 3 separately for imports and exports as in the baseline estimation.

I show the results of the PPML estimation in Table 3.[24] In columns 1 and 3, I estimate the effect of immigrants on import and export confiscation values, respectively, without including the first-stage residuals. In columns 2 and 4 I add the first-stage residuals.

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

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

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

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

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

[25] Using $\hat{\beta} = 0.481$ from column 2 in Table 3 and a mean bilateral immigrant population of 942, we have:

Turning to the effect of immigrants on the value of drug exports, the estimated coefficient is 0.644 (SE=0.35). This estimate implies that a 10% increase in the number of immigrants relative to the mean raises the value of drugs trafficked to the immigrants' origin country and confiscated locally by 3%.[26] Consistent with my earlier results, the effects of immigrants on imports and exports are statistically indistinguishable.

## 3.8 Preferences for Drugs and Trade Costs

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

**Immigrant Preferences.** Atkin (2013) and Bronnenberg et al. (2012) find that immigrants and consumers in the immigrants' home country may exhibit similar preferences for consumption goods. If these similar tastes also apply to illicit drugs, more drugs may be trafficked from the immigrants' origin country. However, such a story would require retail drug consumers to have an implausible combination of tastes and information. Consider an immigrant from Venezuela who consumes cocaine. This immigrant would need to be able to distinguish street cocaine based on which country it was trafficked from (not produced in). However, since the modifications to cocaine generally occur close to the point of production, and in any case do not differ much based on production location, it is unlikely that the immigrant's utility from consuming the cocaine would differ much based on which country the cocaine was trafficked through.

I also compare drug use between immigrants and native-born Spaniards and find that immigrants consume drugs at a substantially lower rate. Using the EDADES data introduced in Section 2.3 for the years 2005 through 2015, I find that 22% of those born outside of Spain have ever consumed cannabis, cocaine, heroin, or amphetamines compared to nearly 35% of native-born Spaniards. Taken together, these facts suggest immigrants bringing the demand for drugs from their home country with them to Spain are unlikely to explain my baseline results.

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

[26] Using $\hat{\beta} = 0.644$ from column 4 in Table 3 and a mean bilateral immigrant population of 942, we have: $\frac{C_{d,o}^{2011-2016}[M_{o,d}^{2011}=1.1\times 942]}{C_{d,o}^{2011-2016}[M_{o,d}^{2011}=942]} - 1 = \exp\left(0.644\left(\ln\left(1+\frac{1.1\times 942}{1000}\right) - \ln\left(1+\frac{942}{1000}\right)\right)\right) - 1 = 0.03.$

**Trade Costs.** Immigrants may increase illegal trade in much the same way they raise legal trade. Immigrant networks can reduce information and search frictions for trade between two locations, since trust may be greater within nationality and information travels more smoothly within nationality group (Gould, 1994; Felbermayr et al., 2015). Additionally, immigrant networks raise the cost of opportunistic or cheating behavior by firms within the nationality network, who can be punished for bad behavior by being shunned from business within the network (Rauch and Trindade, 2002). Finally, the qualitative studies summarized in Section 2.1 demonstrate ways in which social connections between immigrants can facilitate trafficking by reducing trade costs.

If immigrant preferences drove the trafficking of drugs, then we would expect immigrants to increase imports of illegal drugs. However, I find that immigrants raise both illegal drug imports and exports. The rise in exports to the immigrants' origin country therefore suggests that immigrants' reduction of bilateral trade costs is more salient for explaining my results.

## 3.9 Effect Heterogeneity

### 3.9.1 Drug-Hub Level of Immigrants' Origin Country

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

In Panel A of Appendix Table D.2, I show the estimated coefficients. I find that origin countries that 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. Column 1 shows that as a country sends a larger fraction of global illegal drug exports, the more likely its migrants will facilitate illegal drug importing to Spain. Column 3 shows that as a country ranks higher on global illegal drug exports, the more likely are its migrants to facilitate drug imports to Spain. I also find some evidence that immigrants from drug hub countries facilitate the export of illegal drugs to their home country, as shown in column 4.

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

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

### 3.9.2 Production Origin vs. Intermediary

To gauge the extent to which intermediary countries are important for trafficking illegal drugs, I examine heterogeneity of the baseline results to whether the country of origin is a known producer of illegal drugs. I focus on cocaine, which, as described in Section 2.1, is produced primarily in just a few countries in the world, whereas the other major drug trafficked in Spain, cannabis, is produced in nearly every country in the world. Therefore, cocaine coming into Spain from countries outside the three major producers (Bolivia, Colombia, and Peru) are being trafficking through intermediary countries.

I estimate this heterogeneity by interacting the *Log Immigrants* 2011 variable with an indicator for whether the country of the immigrants' origin $o$ is a major cocaine producer. I show the results in columns 5 and 6 of Panel A of Appendix Table D.2. I find that immigrants coming from major cocaine producers are more likely to cause an increase in cocaine imports. In particular, the coefficient for immigrants from major cocaine producers is over 50 percent larger than for immigrants from non-producers, and the effects are statistically different. As a placebo test, I re-run the estimation on cannabis imports and find a similar (and statistically indistinguishable) effect size between cocaine producers and non-cocaine producers. These results suggest that, while direct shipments from the production region are more likely, shipping the drugs through intermediate countries also frequently occurs.

### 3.9.3 By Mode of Transportation

I next analyze how drug trafficking vary across the mode of transportation in which the confiscation occurred. Drugs can be transported by air, land, or sea. By air, drugs can arrive via passengers disembarking or through air-flown freight or mail. By sea, drugs can arrive hidden in legal trade cargo containers at ports or via speedboat transported from nearby foreign locations, such as Morocco, Gibralter, or Portugal. By land, the drugs can arrive from Portugal, France, Morocco (where Spain's enclave cities of Ceuta and Mellila in North Africa share a land border with Morocco), or the United Kingdom (via Gibraltar).

I show the effects of immigrants on trafficking differentiated by mode of transport in Panel B of Appendix Table D.2. I find that immigrants raise illegal drug imports across all three modes of transportation, but by air the most. On the export side, the effects of immigrants are similar across different modes of transportation, though the effect is statistically significant only for exports across land.

# 4 Enforcement Intensity and General Equilibrium Responses

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

## 4.1 Enforcement Intensity

As with many studies of illegal behavior, I only observe drugs which are confiscated by police. The resulting dataset of drug confiscations is therefore a result of willful actions taken by criminals to hide their actions and of police to uncover those actions (Pinotti, 2020). In my baseline gravity estimation, I use a set of country and province fixed effects to control for policing enforcement intensity specific to each Spanish province (and common across all origins) as well as for enforcement intensity specific to each origin country (but common to all Spanish provinces). Moreover, in Section 2.3 I showed that drug confiscations correspond to drug use and availability at the *province level*, suggesting that confiscations correspond to actual illegal drug imports.

In this section, I conduct an additional exercise at the *country-province-pair level* to assess the extent to which variation in bilateral enforcement intensity drives my baseline results from Section 3.5. This exercise addresses the concern that variation in policing enforcement intensity might respond to variation in the size of the bilateral immigrant population. If, as the bilateral immigrant population rises, police enforcement of anti-drug trafficking laws against that bilateral immigrant population rises in tandem, then import confiscations may increase as a result of greater law enforcement scrutiny rather than because immigrants are trafficking more drugs. For example, a larger Moroccan immigrant population in Barcelona might make it easier for police to find informants in the Moroccan immigrant population, even if that larger population induces no increase in illegal drug imports from Morocco.

To test for the extent to which such bilateral enforcement intensity affects my baseline estimates, I start from the intuition that for country-province pairs near the extensive margin of trafficking drugs, enforcement changes caused by variation in the number of immigrants will not substantially affect confiscations. To formalize the intuition, note that confiscations are a product of enforcement intensity and actual drug flows:

$$C_{o,d} = E_{o,d} D_{o,d} \tag{4}$$

where $C_{o,d}$ is the value of drugs confiscated between $o$ and $d$, $E_{o,d}$ is the fraction of drugs confiscated, and $D_{o,d}$ is the actual flow of drugs from $o$ to $d$. Taking the derivative of equation 4 with respect to the number of immigrants, I obtain

$$\frac{dC_{o,d}}{dM_{o,d}} = E_{o,d}\frac{\partial D_{o,d}}{\partial M_{o,d}} + D_{o,d}\frac{\partial E_{o,d}}{\partial M_{o,d}} \tag{5}$$

Conditional on the set of fixed effects $(\alpha_o, \alpha_d)$ in my baseline gravity estimation of equation 1, I implicitly assume that $\frac{\partial E_{o,d}}{\partial M_{o,d}} = 0$. This assumption allowed me to estimate the object of interest, $\frac{\partial D_{o,d}}{\partial M_{o,d}}$. Alternatively, I could fix $D_{o,d}$ to be near zero and instead relax the assumption to $\frac{\partial E_{o,d}}{\partial M_{o,d}} < \infty$.[29] The challenge, however, is subsetting my sample to country-province pairs for which actual drugs trafficked $D_{o,d}$, which I do not observe, are near zero.

I construct a prediction of actual bilateral flows $D_{o,d}$ based upon a leave-out measure of confiscations. The intuition of the predictor works as follows: suppose Barcelonan police more intensively enforce anti-drug trafficking laws against Moroccan immigrants (relative to other provinces or other nationalities) due to their large local group size. Then data on confiscations in Barcelona will include a disproportionate sample of drugs coming from Morocco. To strip out this discrimination from the bilateral confiscations data, I look at how (i) Barcelona confiscates drugs coming from outside Africa, and (ii) how other provinces outside Catalonia confiscate drugs coming from Morocco.

Specifically, to predict when actual flows $D_{o,d} \approx 0$, I use a similar leave-out push-pull structure for confiscations between 2011 and 2016 as I did for immigrant inflows in equation 2:

$$\hat{D}_{o,d} = C_{o,-a(d)} \times \frac{C_{-c(o),d}}{C_{-c(o)}} \tag{6}$$

where $C$ denotes the number of confiscation events.[30] $\hat{D}_{o,d}$ interacts the number of confiscations of drugs originating from $o$ but confiscated outside the autonomous community of $d$ with the fraction of all drug confiscations from outside $o$'s continent confiscated in $d$. Implicit in this formulation is the assumption that (1) on average, law enforcement in province

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

[30] I focus on discrete confiscation events instead of the dollar value of drugs confiscated. This is due to the fact that the number of events if a better indicator of being on the extensive margin than the dollar value of confiscations because a single drug shipment can have any value of drugs contained within it.

$d$ will discriminate differently against immigrants from continents outside of $c(o)$, and (2) on average, law enforcement in other autonomous communities will discriminate differently against immigrants from $o$.

To gauge the extent to which enforcement intensity variation may affect my results, I re-estimate equation 1 for the subset of observations for which I predict that $D_{o,d} \approx 0$. I show results in Table 4 subsetting to bilateral links that I predict having at most 1 confiscation event. While the point estimate falls when subsetting to the sample predicted to be on the extensive margin, the extensive margin estimate in column 2 remains statistically significantly positive, suggesting enforcement variation cannot fully explain my bilateral results. For the results on exports shown in columns 3 and 4, I find a modest decline in the coefficient, with a loss of statistical significance in column 4.

Table 4: Effect of Immigrants on Drug Confiscations: Extensive Margin

| | Imports Confiscations (Dummy) | | Exports Confiscations (Dummy) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log immigrants 2011 | 0.163*** | 0.0976** | 0.0579* | 0.0199 |
| | (0.0455) | (0.0426) | (0.0348) | (0.0239) |
| Observations | 5564 | 5183 | 5564 | 5463 |
| $R^2$ | 0.047 | 0.035 | 0.019 | 0.010 |
| Country FE | Y | Y | Y | Y |
| Province FE | Y | Y | Y | Y |
| Ln dist | Y | Y | Y | Y |
| 1st-stage F-statistic | 152.4 | 304.6 | 152.4 | 47.9 |
| Sample | All | $\leq 1$ predicted confiscations | All | $\leq 1$ predicted confiscations |

*Notes:* The table presents coefficient estimates from IV regressions of equation 1 at the country-province level. I instrument for the immigrant population measure using $\{IV^D_{o,d} = I^D_{o,-a(d)} \times I^D_{-c(o),d}/I^D_{-c(o)}\}_{1991-2001,2001-2011}$, their interaction across decades, and squared terms as the excluded instruments. In column 2, I subset the sample to the set of country-province pairs for which the number of predicted confiscations (defined in equation 6) is less than or equal to 1; I do the same for predicted export confiscations in column 4. Standard errors are clustered by country in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

## 4.2 General Equilibrium Responses

While I have shown that immigrants increase drug trafficking with their home country, this effect may be offset by general equilibrium adjustments to immigrant-induced trafficking. For example, trafficker immigrants from one country may reduce their trafficking in response to more immigration from another country. If such adjustments offset the effect of immigrants on trafficking, then there should be no effect when aggregating across origin countries. To assess the strength of the general equilibrium response, I conduct two exercises.

First, in Figure 5, I plot the evolution of drug import confiscations over time between low and high immigration Spanish provinces. If general equilibrium reallocation were dominant, one would expect that low immigrant population provinces to experience a decline in drug imports to offset an increase in high immigrant population provinces. In contrast, the plot demonstrates that provinces with a below-median immigrant population in 2000 experience no significant change in drug confiscations, while high immigrant population provinces experienced significant increases in total confiscations. While a lack of controls and exogenous variation means alternative stories can explain the patterns displayed in the chart, the results are nonetheless suggestive that general equilibrium reallocation effects may not override the well-identified causal effects estimated using the gravity equation in Section 3.

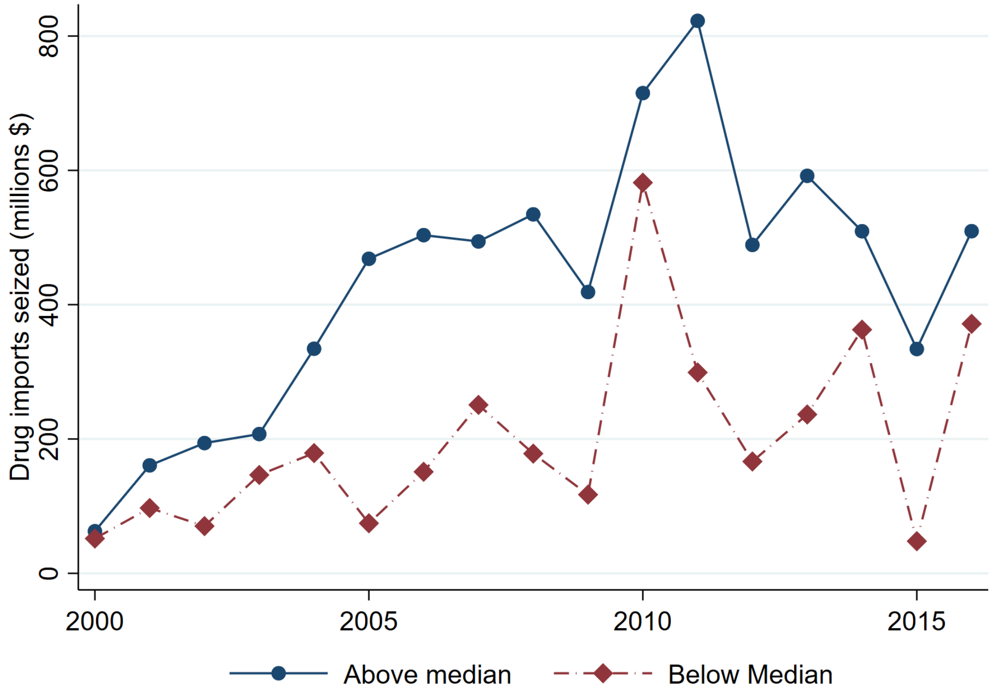
As a second exercise, I regress the immigrant population size on drug market activity at the province level. I start by estimating the effect of immigrants on confiscations of illegal drugs, illegal drug use, and drug trafficking arrests with a panel of Spanish provinces. In particular, I estimate

$$\frac{Y_d^t}{Pop_d^t} = \alpha_d + \alpha^t + \beta \frac{Migr_d^t}{Pop_d^t} + \epsilon_d^t \tag{7}$$

for some measure $\frac{Y_d^t}{Pop_d^t}$ of per capita illegal drug activity and the fraction of immigrants in the population $\frac{Migr_d^t}{Pop_d^t}$ for province $d$ in year $t$. I also control for province and year fixed effects and cluster standard errors at the autonomous community-by-year level.

There may still be factors affecting both immigration and drug smuggling into a province net of these fixed effects. For example, if immigrants are attracted to regions with rising incomes, and drug traffickers also establish connections to regions with rising incomes (and therefore an expanding market for drugs), then a spurious correlation between immigration and drug trafficking may arise. Therefore, I instrument for the immigrant population using a version of the popular ethnic enclave instrument developed by Card (2001). Specifically, I instrument for the immigrant population share with

Figure 5: Drug Confiscations and Local Immigrant Population




*Notes*: The figure plots the evolution over time of the value of import drug confiscations, separately for the 26 Spanish provinces with an above median immigrant population as of 2000 (blue solid line) and the equal number of Spanish provinces with a below median immigrant population in 2000 (red dash-dot line).

$$IV_d^t = \frac{1}{\widehat{Pop}_d^t} \sum_o \frac{Migr_{o,d}^{1981}}{Migr_o^{1981}} Migr_o^t \tag{8}$$

where $Migr_o^t$ refers to the number of immigrants from $o$ living in Spain in year $t$. $\widehat{Pop}_d^t$ is the predicted population of province $d$ in year $t$. I predict the population as follows, following Mayda et al. (2022). First I predict immigrant inflows summing over origin countries the interaction between the initial immigrant population share and the national change in immigrants from that origin[31]: $\Delta \hat{X}_d^t = \sum_o \frac{X_{o,d}^{1981}}{X_o^{1981}} (X_o^t - X_o^{t-1})$ for $X$ referring to either native-born or immigrants and for each year of data available. Next, I add these predicted immigrant flows and native population changes to the observed 1981 migrant or native populations, respectively. Summing the predicted migrant and native populations together yields $\widehat{Pop}_d^t$

[31]Following Card (2001) and Mayda et al. (2022), I collapse origin countries into 16 groups. These groups are the top 8 immigrant sending countries (Italy, Venezuela, Argentina, United Kingdom, Portugal, France, Morocco, and Cuba), and the remaining countries in Western Europe, Eastern Europe, South American, Central American and the Caribbean, the U.S. and Canada, Africa, Asia, and Australia and Oceania.

for each province and year. I use data from the years 2006 to 2016.[32]

I show the results of estimating equation 7 in Table 5 for a variety of indicitors of the local illegal drug market. I show the first-stage regression results in column 1. The ethnic enclave instrument defined in equation 8 positively and statistically significantly predicts the local share of immigrants. I next estimate the effect of immigrant population share on the per capita value of drugs confiscated in province $d$ in year $t$ for imports (column 2) and exports (column 3). Column 2 of Table 5 shows the result for imports, and in column 3 for exports. I find that an increase in the local migrant population share of 10 percentage points raises per capita confiscations of illegal drug imports by \$83 (SE=\$45) and of exports by \$11 (SE=\$33). These results suggest that more immigrants in a region raises total drug imports into that region relative to other regions..

[32] I start the time series in 2006 in part because the data on drug use does not start until 2005. Moreover, there are several months of zero reported confiscations prior to 2006 (as shown in Figure 6), suggesting that reporting of drug confiscations was not consistent in this earlier period.

Table 5: Effect of Immigrants on Illegal Drug Activity (Province-level)

| | (1) First-Stage: Share immigrants | (2) 2SLS: value imports confiscated per-capita | (3) 2SLS: value exports confiscated per-capita | (4) 2SLS: shr. native-born used drugs last 12 mo. | (5) 2SLS: shr. native-born ever used drugs | (6) 2SLS: native-born drug trafficking arrests per-capita | (7) 2SLS: cannabis plant confiscations per-capita |
|---|---|---|---|---|---|---|---|
| Ethnic Enclave IV | 8.546*** | | | | | | |
| | (2.601) | | | | | | |
| Migr. pop. share | | 838.1* | 111.9 | -0.0391 | 0.831 | -0.00231* | 0.0271 |
| | | (453.7) | (335.7) | (0.343) | (1.092) | (0.00129) | (0.0253) |
| Observations | 572 | 572 | 572 | 260 | 260 | 364 | 50 |
| First-stg. F-stat. | 10.8 | 10.8 | 10.8 | 6.7 | 6.7 | 7.7 | 7.8 |

*Notes:* The table presents coefficient estimates from IV regressions of equation 7 at the province-year level. I instrument for *Migr. pop. share* using the excluded instrument defined in equation 8, with the first-stage shown in column 1. The dependent variable in column 2 is the value of illegal drug imports and in column 3 exports confiscated per capita. The dependent variable of columns 4 and 5 is the share of native-born Spaniards reporting to the EDADES survey that they used drugs in the last 12 months (column 4) or ever (column 5). The dependent variable of column 6 is the number of Spanish citizens arrested for illegal drug trafficking per capita. Column 7 shows results using the number of cannabis plants seized per capita as the dependent variable, which is only available for a single cross-section. Per capita values are relative to the 1981 province population. Standard errors are clustered at the autonomous community-by-year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

As an alternative measure of local drug supply, I next turn to local illegal drug consumption. I estimate equation 7 with dependent variable of the share of the native-born using illegal drugs, measured using the biennial EDADES survey described in Section 2.3. I find no statistically significant effect of immigrants on the drug use of the native-born as shown in columns 4 and 5 of Table 5, though due to the biennial nature of the survey, the sample size and therefore estimation precision fall significantly.

To get a sense for whether immigrant labor is substituting for the native-born in high-immigration provinces, I examine how per capita native-born drug trafficking arrests change with immigration in column 6. Using a panel of arrests data between 2010 and 2016, I find that increased immigration drives down arrests of native-born Spaniards for drug trafficking, although the coefficient magnitude is small. This result suggests that immigrants may, to a modest extent, push the native-born out of the drug trafficking business.

I finally look at how immigration affects the per capita cultivation of cannabis plants within Spain.[33] As immigration reduces trade costs, one may expect trade to displace local production. Alternatively, an increased labor supply (in the form of immigration) may reduce the costs of production, thereby increasing local cannabis production. I find no statistically significant effect of immigrants on cannabis plant confiscations using a cross-section of plant confiscations data.[34]

# 5 Legal Status, Naturalization, and Trafficking

Immigrants' integration into labor markets and civil society may be hampered when they do not have legal status. This lack of access to the formal labor sector lowers the opportunity cost of crime for immigrants without legal status (Becker, 1968; Ehrlich, 1973). The lower opportunity cost may increase criminal activity among immigrants without legal status, as found empirically by Mastrobuoni and Pinotti (2015), Pinotti (2017), and Freedman et al. (2018), especially in financially motivated crime such as drug trafficking.

To assess whether this intuition holds for drug trafficking, I conduct two exercises. First, I estimate a gravity equation to test the effect of irregular immigrants (those without legal

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

[34]I draw on Alvarez et al. (2016), who assemble a dataset on cannabis plant confiscations based on 2013 press reports and public statements by the Spanish government. 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.

status) and regular immigrants on drug confiscations. Second, I exploit an extraordinary immigrant legalization program in 2005 to estimate an event study.

## 5.1 Measuring the Irregular Immigrant Population

Counting the number of immigrants without legal status can be challenging, as these immigrants are typically missed in standard administrative datasets (Warren and Passel, 1987; Borjas, 2017). Spain, however, offers unique institutional features that facilitate accurate tabulation of this population. In particular, Spain has offered immigrants access to the public healthcare system regardless of one's legal status since the passage of the 2000 Aliens Law (González-Enríquez, 2009).

I take advantage of this institutional feature to impute the number of irregular immigrants in Spain at the country-province-pair level. To do so, 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

$$Irregular\ Migrants_{od} = Population\ Registry\ Count_{od} - Residency\ Permits_{od} \tag{9}$$

and then divide by the total bilateral immigrant population to obtain the fraction of immigrants who have irregular status.[35]

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 measurement error in immigrant legal status may correlate to drug trafficking. However, if the measurement error occurs for a specific nationality across Spain (say, for Chinese immigrants) or for all immigrants in a particular Spanish province, the country and province fixed effects will absorb variation in trafficking induced by such measurement error. Any residual measurement error at the country-province-pair level will bias the estimated coefficients toward zero so long as it is classical.

I impute the irregular immigrant population for set of the origin countries for which I observe bilateral population registry figures and bilateral residency permits in 2011 and the 52 Spanish provinces. I estimate that 20% of immigrants living in Spain are irregular, in line with the estimate from González-Enríquez (2009) for 2008.

[35] For countries within the E.U., I set the number of irregular immigrants to 0.

## 5.2 Gravity Estimation by Legal Status

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

$$Y_{o,d} = \alpha_o + \alpha_d + \beta_{irreg} M_{o,d}^{irreg} + \beta_{reg} M_{o,d}^{reg} + \zeta \ln(Dist_{o,d}) + \varepsilon_{o,d} \tag{10}$$

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

Separating immigrants by legal status introduces another endogeneity issue—differential selection of immigrants into legal status and trafficking—which the baseline leave-out push-pull instrument defined in equation 2 may not address. For example, some immigrants with a higher taste for risk may be more likely to be irregular and participate in illegal drug trafficking. To the extent that this selection is common across provinces for a given nationality, the country fixed effect $\alpha_o$ will absorb such selection. Similarly, if the characteristic is common across immigrants of different nationalities in a given province, the province fixed effect $\alpha_d$ will absorb this common preference for risk-taking.

To address province-country-specific selection into irregularity and drug trafficking, I modify the leave-out push-pull instrument predicting total immigrant inflows to predict immigrant inflows by legal status. In particular, I define the legal status-specific leave-out push-pull instrument as:

$$IV_{o,d}^{D,L} = m_{o,d}^{L} \times IV_{o,d}^{D} \tag{11}$$

for $L \in \{regular, irregular\}$ and decade $D$, where $IV_{o,d}^{D}$ is the baseline leave-out push-pull from equation 2 and $m_{o,d}^{L} = \frac{immigrants_{o,-a(d)}^{2001,L}}{immigrants_{o,-a(d)}^{2001}}$ is the fraction of immigrants with legal status $L$ from country $o$ who live outside the autonomous community of province $d$ back in 2001. I use 2001 as the base year as it was the first year in which irregular immigrants were incentivized to enroll in their local population registry in order to qualify for public health care due to the passage of the 2000 Aliens Law (González-Enríquez, 2009). The instrument interacts variation across three dimensions: (i) immigration from various origin countries, (ii) immigration to various Spanish provinces, and (iii) the propensity of immigrants to have legal status $L$ at the country-province level.

The identification restriction is that there are no confounders persistent from 2001 to 2011 and present in both province $d$ and another province outside $d$'s autonomous community at the country-province level which drives selection of immigrants into both irregular status and drug trafficking. For example, suppose we want to predict the fraction of irregular Moroccan immigrants living in Barcelona in 2011. $m^L_{o,d}$ uses information on the legal status of Moroccan immigrants outside Catalonia (the autonomous community of Barcelona) back in 2001 to predict the 2011 legal status of Moroccans in Barcelona. The exclusion restriction is violated if, say, Moroccans in Madrid in 2001 were driven into irregularity and drug trafficking by the same confounder (e.g., a preference for risk-taking) that drove Moroccans in Barcelona in 2011 into irregularity and trafficking. This endogeneity will meaningfully affect the estimation if a non-trivial share of Moroccans outside Catalonia live in Madrid in 2001 and the confounder acts disproportionately on Moroccans in Madrid than on Moroccans elsewhere (i.e., it is not absorbed by the Moroccan fixed effect).

I show the results of estimating equation 10 in Table 6. I find that a 10% increase in the bilateral *irregular* immigrant population raises the likelihood of an illegal drug import confiscation by 0.4 percentage points. By contrast, a 10% increase in the *regular* immigrant population raises the likelihood of illegal drug imports by 0.3 percentage points, though the estimated coefficient is statistically insignificantly different from 0.[36] I also find that regular immigrants increase illegal drug exports, while irregular immigrants reduce them, as shown in column 2 of Table 6.

The import results are therefore consistent with the Becker-Ehrlich model of crime: immigrants with worse labor market opportunities due to their legal status are more likely to facilitate illegal drug trafficking. However, the results for exports are puzzling when interpreted through the lens of the Becker-Ehrlich model of crime.

Instead, I point to E.U.-specific institutions governing migration and trade. First, I note that the primary export destinations of drugs leaving Spain are other European Union member states (see Figure D.6). Immigrants from E.U. countries cannot be irregular in Spain, and therefore regular immigrants neccesarily will play a larger role in facilitating exports out of Spain and into Europe. Second, much of the within-Europe trafficking is conducted by small wholesale distribution companies with a fleet of trucks. Taking advantage of the E.U.'s borderless environment facilitates the flow of illegal goods as much as it does legal goods.[37]

[36] Using $\hat{\beta}^{Irreg} = 0.249$ from column 1 and mean value of bilateral irregular immigrant population of 204, I find that $\mathbb{1}\left[C^{2011-2016}_{o,d} > 0 | M^{2011}_{o,d} = 204\right] = 0.249\left(\ln\left(1 + \frac{204 \times 1.1}{1000}\right) - \ln\left(1 + \frac{204}{1000}\right)\right) \approx 0.0041$ and for $\hat{\beta}^{Reg} = 0.0715$ and a mean of bilateral regular immigrant population of 802 this is 0.003, and statistically indistinguishable from 0.

[37] Fukumi (2008) notes that "the introduction of the Schengen Agreement in 1985, and the full implementation of the Schengen Treaty in 1995 opened a window of opportunity to cocaine traffickers because

Table 6: Effect of Immigrants by Legal Status on Drug Confiscations

| | Dummy for Any Drug Confiscations | |
|---|---|---|
| | Imports | Exports |
| Log regular immigrants 2011 | 0.0715 | 0.146*** |
| | (0.0582) | (0.0333) |
| Log irregular immigrants 2011 | 0.249*** | -0.174*** |
| | (0.0606) | (0.0419) |
| Observations | 5200 | 5200 |
| SW 1st-stg. F-stat. (regular immigrants) | 34.4 | 34.4 |
| SW 1st-stg. F-stat. (irregular immigrants) | 44.4 | 44.4 |

*Notes:* The table presents estimates of IV regressions by legal status at the country-province level. The dependent variable is a dummy for whether any confiscation occurred, separately for imports (column 1) and exports (column 2). I instrument for the immigrant population by legal status using equation 11 as well as the interaction across decades and squared terms. SW F-statistics refer to those described by Sanderson and Windmeijer (2016). Standard errors are clustered by country in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Such companies are much more likely to be owned and operated by someone with legal status, either a native or regular immigrant. While the negative coefficient on irregular immigrants in column 2 is surprising, it may be a result of the fact that there are few irregular immigrants from the top non-E.U. export destinations (e.g., Turkey) while those countries with many irregular immigrants in Spain typically only send drugs to Spain but rarely receive any exports (e.g., Latin America and Morocco).

These results suggest immigrant legal status is an important factor shaping immigrants' role in drug trafficking. However, 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.

### 5.3 2005 Mass Regularization Event Study

In 2005, Spain conducted the largest mass regularization of immigrants in its history, with over half a million immigrants obtaining legal status. Immigrants who were registered with their local council in the population registry as of August 8, 2004, were offered a work contract of at least six months (three months if in agriculture), and had no criminal record in their home country or in Spain, were eligible to apply for regular status, usually through their prospective employer (González-Enríquez, 2009). Moreover, the reform was a surprise

it enabled free movement within a major part of Western Europe." (p. 50) She further argues that drug traffickers often launder money by buying import and export companies, commodity trading businesses, and cargo businesses, which are all useful in transporting illegal drugs (p. 54).

as a result of the 2004 Madrid bombings shortly before the 2004 elections resulted in an upset victory for the pro-immigrant regularization party (Monras et al., 2021). The 2005 regularization led to a sharp increase in the number of work authorizations granted to immigrants in Spain, as shown in Figure D.11.

To better understand the effects of the regularization, I estimate a simple event study at the country-by-quarter level. The event study unit of aggregation differs from the estimates presented in Section 3.2 in that I use higher frequency quarterly variation in drug confiscations and aggregate from the province-by-country level to the country level. I do so for three reasons. First, I use nationality-level aggregation because the policy differentially affected immigrants depending on their country of origin. For example, immigrants from the E.U. were not impacted by the policy since the Schengen Agreement precludes irregularity. Second, at the bilateral level, confiscations can occur highly irregularly, with no confiscations for several years followed by a year with one massive confiscation. Such volatility is likely more a result of variation in enforcement luck rather than changes in the actual flow of illicit drugs, and therefore reflects measurement error. To smooth out this variation and thereby obtain more precise estimates, I aggregate to the country-quarter level. Third, to better establish a causal relationship between the legalization policy and any change in drug trafficking, I exploit the rich detail in the timing of drug confiscations and look at confiscations at a quarterly frequency.

I estimate the event study using the equation

$$Y_o^t = \sum_{t \neq 2004q4} \theta^t \times Frac.\ irregular_o^{2003} + \delta_o + \delta^t + \epsilon_o^t \qquad (12)$$

where $Frac.\ irregular_o^{2003}$ is the fraction of immigrants in 2003 without legal status, as imputed using equation 9. I estimate the event study for the years 2000 through 2008, choosing the end-year cutoff of 2008 to avoid conflating any effects with the Great Recession.

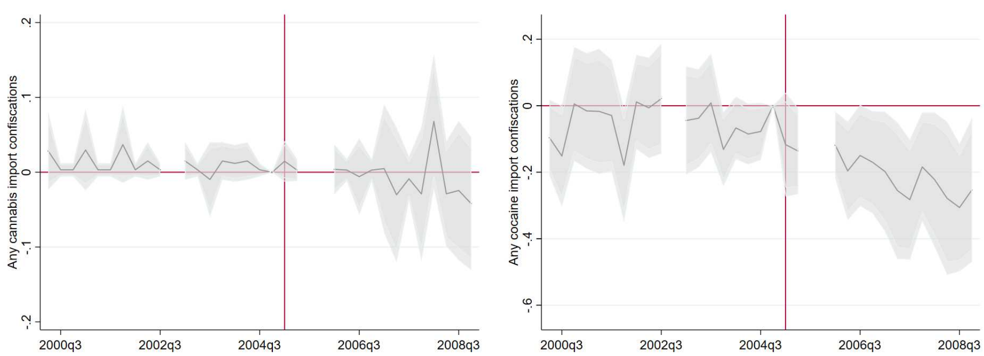
I plot the $\theta^t$ coefficients in Figure 6 with the dependent variable a dummy for whether any import confiscation occurred. I show the 2005 regularization reduced the likelihood of any import drug confiscation and remained lower thereafter. Moreover, this decline came primarily from reductions in cocaine confiscations, as shown in Figure 7, with no change observed in cannabis confiscations. I find a modest increase in export confiscations, as shown in Figure D.12, consistent with the gravity results from Section 5.2.[38] The effects of the regularization on exports are concentrated in cocaine, just as I find for imports.

[38] However, for exports, the pre-event variation is not statistically indistinguishable from 0, unlike for imports.

Figure 6: Effect of 2005 Immigrant Regularization on Drug Imports


*Notes*: The figure shows an event study plot of the effect of the 2005 immigrant regularization on whether any drug imports were confiscated locally. Plot is estimated using equation 12. The dark grey area shows the 90% confidence interval while the light grey area shows the 95% confidence interval.

Figure 7: 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 import confiscations of cannabis (on the left) and cocaine (on the right). The dependent variable is whether any drugs were confiscated coming from the origin country in that quarter. Plots are estimated using equation 12. The dark grey area shows the 90% confidence interval while the light grey area shows the 95% confidence interval.

Immigrants' improved labor market opportunities as a result of the legalization program may partially explain my results. Monras et al. (2021) find that the 2005 legalization substantially improved immigrants' labor market outcomes by facilitating their entry into sectors with low levels of informal employment.

To explain the differential effect of the policy on cocaine—coming primarily form Latin America—versus cannabis (which comes primarily from Morocco) I note the various ways in which Spanish institutions treat Latin American immigrants more favorably than Moroccan immigrants. For example, for the 2005 mass legalization, Latin Americans made up about half of successful applicants for legalization whereas Moroccan applicants made up about 12%. Moreover, the likelihood of having a sucessful application varies by immigrant origin, with Moroccans experiencing a 9 percentage points lower likelihood of successfully applying for legalization as compared to Latin American immigrants.[39] Moroccan immigrants also face more hurdles to obtain Spanish citizenship, being required to be in the country legally for ten consecutive years. In contrast, Latin American immigrants are only required to be present for two consecutive years before becoming eligible for citizenship. Such policies have led to a divergence in citizenship acquisition by origin region, as shown in Figure D.13. Finally, Latin American immigrants are more likely to natively speak Spanish and thus face an easier time culturally and economically assimilating into Spanish society.

Overall, the event study results suggest that granting legal status to immigrants plays an important role in reducing drug trafficking, especially for those immigrants facing the easiest time assimilating into Spanish society. Taking the average of the coefficients from 2005 to 2008 for the event study estimated on the extensive margin of illegal imports suggests that granting 10% of immigrants legal status reduces the likelihood of import trafficking of any drug by 1.4 percentage points and of cocaine specifically by 2 percentage points.

# 6 Conclusion

The effect of immigration on crime has long been a controversial political issue. In this paper, I contribute to this debate by causally estimating the effect of immigrants and immigrant legal status on international illegal drug trafficking. I find that international immigrants play an important role in shaping international drug trafficking, both on the import and export margin. Two mechanisms drive these effects: immigrants' social connections with their origin country and immigrants' legal labor market opportunities, as proxied for by their legal status. I find that granting immigrants legal status can reduce illegal drug imports.

The results presented here have significant relevance to ongoing debates on immigration policy in the United States and around the world. In particular, as many European countries and the United States discuss providing some form of amnesty and a path to citizenship to their large populations of undocumented immigrants, this paper offers an additional potential benefit to society from such amnesties. Providing amnesty may be cheaper to administer than attempting to keep irregular immigrants from entering the country, such as by 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.

[39] Calculations based on Table VI of González-Enríquez (2009).

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

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

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# A Data Appendix

## A.1 Drug Confiscations

As discussed in Section 2.2, I draw the data on drug confiscations from the United Nations Office of Drugs and Crime (UNODC). For my baseline estimation, I use data on confiscations from Spain, which reports high-quality drugs data. However, in some exercises (in particular that of Section 3.9.1) I utilize data from all countries in the dataset. I next describe in greater detail the UNODC data and the data cleaning procedures I apply to do.

**Drug Groupings** The UNODC data on drug confiscations are reported in a variety of unit amounts and drug types. In the empirical analysis, I focus on four primary drug types: cannabis, cocaine, amphetamines, and heroin. Because drug confiscations are reported for a variety of drug types, I condense these types into aggregated groupings according to Table A.1.

**Comparability of Confiscation Amounts** Comparing confiscated amounts even within drug groupings is challenging due to their imperfect substitution. For example, opium and heroin are two distinct drugs with different street prices. To make confiscations comparable across drug types and the reported unit of seizures, I proceed in three steps. First, I translate all units into kilograms. Second, I apply a deflation term to the imputed kilograms depending on what stage in the production chain the drug type is (e.g., cocaine base is an input into consumable cocaine). Third, I convert the kilogram measure into a dollar value using a Spanish survey of drug prices reported by the UNODC.

The first step, translating units into kilograms, is straightforward when a mass or weight unit is provided. When a mass value is not provided (e.g., I see the number of capsules or liters of a confiscation), I turn to United Nations and scientific papers on the estimated average conversion rates between different units of drugs and their consumption-grade equivalent in kilograms. For amphetamines and methamphetamines, I apply conversion rates summarized in Table A.2. Following the UNODC (p. 39, 2017), I convert 1 liter into 1 kilogram, and a cannabis plant into 100 grams.

Additionally, I convert drugs higher up the supply chain—i.e., inputs into final consumable drugs—into an equivalent amount of the drug lower down the supply chain. For example, heroin is derived from opium poppies, with about 9.6 kg of opium producing 1 kg of heroin (UNODC and Afghan Ministry of Counter Narcotics, 2015). I therefore convert opium poppies into their heroin equivalent. I also convert morphine base into heroin, following Figure II of Zerell et al. (2005), which states that 7.8 kg of morphine base can be convered into 3.9

Table A.1: Author's Drug Groupings

| **Drug Group (Analysis Data)** | **Drug Type (Raw Data)** |
|---|---|
| Cannabis | Cannabis<br>Cannabis herb (Marijuana)<br>Cannabis leaves<br>Cannabis oil<br>Cannabis plants<br>Cannabis pollen<br>Cannabis sativa<br>Cannabis resin<br>Cannabis seeds |
| Cocaine | Cocaine<br>Coca plant<br>Coca seeds<br>Coca leaf<br>Coca paste<br>Cocaine base<br>Cocaine HCL |
| Heroin | Heroin<br>Heroin base<br>Extract from Opium poppy<br>Morphine<br>Opium<br>Acetylated Opium |
| Amphetamines | Amphetamine<br>Liquid methamphetamine<br>Methamphetamine |

Table A.2: Drug Conversion Rates for Amphetamines and Methamphetamines (doses to milligrams)

| **Region** | **Amphetamine** | **Methamphetamine** |
|---|---|---|
| Africa | 250 | 250 |
| Asia (excluding Middle East/Southwest Asia) | 250 | 90 |
| Europe | 253 | 225 |
| Central and South America and Caribbean | 250 | 250 |
| Middle East/Southwest Asia | 170 | 250 |
| North America | 250 | 250 |
| Oceania | 250 | 250 |

*Notes*: The table displays conversion rates of individual tablets, pills, capsules, or doses into milligrams following the table from page 38 of UNODC (2017). For example, confiscations of a single dose of amphetamines or methamphetamines in Africa are converted into 250mg.

kg of white heroin.

**Cleaning the Geography of Confiscations** The UNODC data provides data on the "Place" of the confiscation, which may refer to the province or municipio. I match municipios to their province using the IPUMS crosswalk between regions within Spain. I drop municipios that I cannot match to a Spanish province, either because of some typos in the municipio name or because the place name does not correspond to a province (e.g., international waters).

**How Spain Fills in the UNODC Data** Spain's Centro de Inteligencia contra el Terrorismo y el Crimen Organizado (CITCO) sends information on individual drug confiscations regularly to the UNODC. These data are assembled by the Sistema Estadístico de Análisis y Evaluación sobre Crimen Organizado y Drogas (SENDA), using information furnished by the Policía Nacional, Guardia Civil, and the Departamento de Aduanas e Impuestos Especiales. However, drug confiscations conducted by local or municipio police are also included so long as they are reported to the National Police or Guardia Civil for drug trafficking crimes.

The process to determine the country of origin is described by CITCO as follows:

> "La atribución de las drogas a un país de salida, se realiza siempre y cuando sea posible, en función de los datos extraídos de la investigación, tales como la manifestación voluntaria y posteriormente comprobada de los detenidos, la documentación intervenida, el origen de los contenedores o de la mercancías entre las que se ocultaba la droga, origen del vuelo del correo humano interceptado, etc.
>
> En el caso concreto de los contenedores marítimos, por parte de los agentes investigadores, también se analiza la información existente en los documentos necesarios para llevar a cabo este tipo de transporte, es decir, el packing list, el bill of lading, la factura comercial, el certificado de origen, el despacho de aduanas y la carta de crédito, entre otros.
>
> En el caso de las narco lanchas que transportan resina de hachís y, que son interceptadas e intervenidas en el Mar Mediterráneo en el Estrecho de Gibraltar, tanto en aguas territoriales españolas como en la costa andaluza, salvo prueba en contrario, se considera que su país de origen es Marruecos.
>
> Si se trata de narco-lanchas que transportan cocaína y, que son interceptadas en Océano Atlántico frente a las costas gallegas, por regla general, el país de origen se determinará cuando sea posible, en base a la información obtenida de

las investigaciones que se hayan llevado a cabo."[40]

In particular, as discussed in Section 2.2, attribution of drugs to their origin and destination is done via investigation following confiscations, covering a range of evidence seized (e.g., persons detained and any relevant documentation). For example, 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. While investigations are conducted after every confiscation event, boats with hashish resin intercepted in the Strait of Gibralter or on the Andalusian coast are assumed to come from Morocco unless proven otherwise.

**Comparison of UNODC Data Across Countries** In my baseline analysis I focus on the country of Spain due to its higher quality reporting of illegal drug confiscations to the UNODC. I graphically depict Spain's superior data reporting in Figure A.1. The figure shows that Spain reports an unusually high number of confiscations in which the country of trafficking origin is reported (vertical axis). Moreover, Spain almost always reports the location within Spain in which the confiscation occurred (horizontal axis). Combined, these two dimensions of data quality make Spain an outlier within the UNODC data on individual drug seizures.

## A.2 Measuring Immigration in the Spanish Census

To measure bilateral immigrant populations and inflows in my baseline cross-sectional gravity analysis (Section 3), I employ the decennial Spanish census. I measure the number of immigrants from an origin country by counting the number of individuals with citizenship from that origin country.[41] In the case of dual citizens, the non-Spanish country of citizenship is reported.

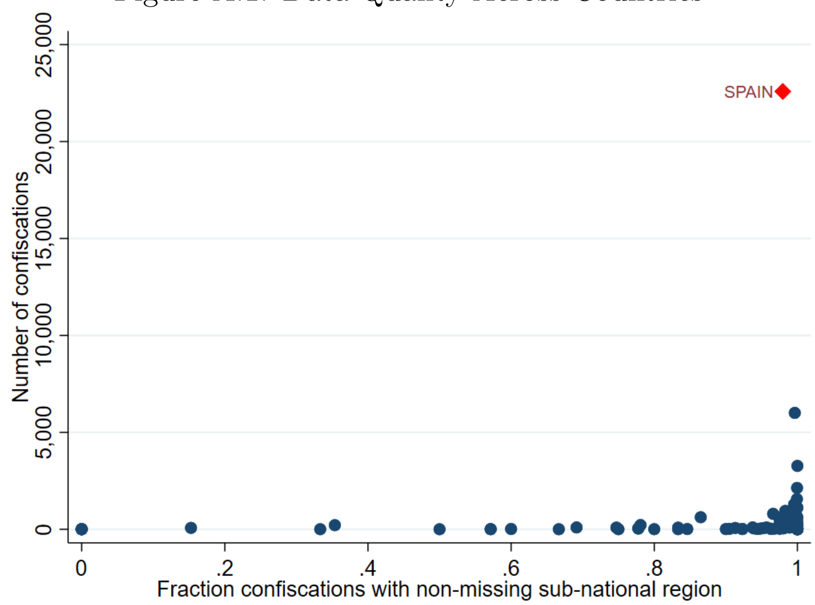
To construct the leave-out push-pull instrument I also use data from the Spanish Census on immigrant inflows. To measure bilateral inflows for each decade, I count the number of immigrants who arrived from the origin country and reside in the Spanish province within the last 10 years. For example, to count the inflows from Morocco to Barcelona between 1991 and 2001, I refer to the 2001 Spanish Census and count the number of Moroccans living in Barcelona who report having arrived in the previous 10 years.

Because the set of immigrant origin countries reported varies across census waves, I aggregate countries into groups consistent across both the 2001 and 2011 Spanish Censuses.

[40] Comes from government response to information request composed by the author.

[41] In unreported regressions I find that changing the definition of immigrant to be based on country of birth has virtually no effect on my results.

Figure A.1: Data Quality Across Countries




*Notes*: The chart plots the relationship between the number of confiscations reported to the United Nations Office of Drugs and Crime across all years with information on the sending country and the fraction of those confiscations with information on the sub-national region of the confiscation across countries. Spain stands out as one of the highest-quality reporting countries in the UNODC data.

In both waves I observe 102 individual origin countries, and group remaining countries by continent into country groups (e.g., "Other countries, Africa"). In total, I exploit variation across 107 origin regions.[42]

# B Instrumental Variable: Additional Discussion

In my baseline estimation, I instrument for the immigrant population using two decades of predicted immigrant inflows generated by a leave-out push-pull IV, defined as in equation 2. To better understand the variation generated by the IV conditional on $o$ and $d$ fixed effects, I first explain using the simple, non-leave-out version of the instrument (where I drop the decade superscript for notational clarity):

$$\widetilde{IV}_{o,d} = I_o \times \frac{I_d}{I} \tag{B.1}$$

[42]In unreported regressions, my results are robust to dropping the 5 country groups from the estimation.

Controlling for $o$ and $d$ fixed effects, the residual variation of B.1 become

$$\begin{aligned}\hat{\widetilde{IV}}_{od} &= I_o \times \frac{I_d}{I} - \frac{1}{n_o}\sum_o I_o \times \frac{I_d}{I} - \frac{1}{n_d}\sum_d I_o \times \frac{I_d}{I} \\ &= I_o^D \times \frac{I_d}{I} - \frac{I_d}{n_o} - \frac{I_o}{n_d}\end{aligned}$$

where $n_d$ is the number of Spanish provinces and $n_o$ is the number of countries.

Therefore the push-pull IV predicts the bilateral immigrant flows by interacting the number of immigrants pushed out of $o$ with the fraction of immigrants pulled into $d$, net of the average number of immigrants from $o$ per Spanish province ($I_d/n_o$) and the average number of immigrants in $d$ per origin country ($I_o/n_d$). For example, if we want to predict the number of Moroccans going to Barcelona, I would interact the number of Moroccans coming to Spain ($I_{Morocco}$) with the fraction of immigrants across all origin countries coming to Spain who choose to live in Barcelona ($I_{Barcelona}/I$) net of the average number of immigrants in Barcelona per origin country ($I_{Barcelona}/107$) and the average number of Moroccans per Spanish province ($I_{Morocco}/52$). Note that as the number of geographic units (countries or provinces) grows, the fraction of the residual variation of the instrument made up by the push-pull interaction term grows. This holds so long as total immigration to Spain grows at a smaller rate than the number of provinces and countries do. Therefore, asymptotically the instrument net of the fixed effects approaches the baseline instrument: $\lim_{n_o\to\infty,n_d\to\infty} \hat{\widetilde{IV}}_{o,d} = \widetilde{IV}_{o,d}$.

Next, I consider how the above logic applies to the case of my baseline *leave-out* push-pull instrument. Netting out the provincial mean and country mean from equation 2, I obtain:

$$\begin{aligned}\widehat{IV}_{od} &= I_{o,-a(d)} \times \frac{I_{-c(o),d}}{I_{-c(o)}} - \frac{1}{n_o}\sum_o I_{o,-a(d)} \times \frac{I_{-c(o),d}}{I_{-c(o)}} - \frac{1}{n_d}\sum_d I_{o,-a(d)} \times \frac{I_{-c(o),d}}{I_{-c(o)}} \\ &= I_{o,-a(d)} \times \frac{I_{-c(o),d}}{I_{-c(o)}} - \frac{1}{n_o}\sum_o (I_o - I_{o,a(d)}) \times \frac{I_d - I_{c(o),d}}{I - I_{c(o)}} - \frac{1}{n_d}\sum_d (I_o - I_{o,a(d)}) \times \frac{I_d - I_{c(o),d}}{I - I_{c(o)}} \\ &= I_{o,-a(d)} \times \frac{I_{-c(o),d}}{I_{-c(o)}} - \frac{I_d}{n_o}\sum_o \frac{I_o - I_{o,a(d)}}{I - I_{c(o)}} + \frac{1}{n_o}\sum_o (I_o - I_{o,a(d)}) \times \frac{I_{c(o),d}}{I - I_{c(o)}} - \frac{I_o}{n_d}\frac{\sum_d (I_d - I_{c(o),d})}{I - I_{c(o)}} + \frac{1}{n_d}\sum_d I_{o,a(d)} \times \frac{I_d - I_{c(o),d}}{I - I_{c(o)}} \\ &= I_{o,-a(d)} \times \frac{I_{-c(o),d}}{I_{-c(o)}} - \frac{I_d}{n_o}\sum_o \frac{I_o - I_{o,a(d)}}{I - I_{c(o)}} + \frac{1}{n_o}\sum_o (I_o - I_{o,a(d)}) \times \frac{I_{c(o),d}}{I - I_{c(o)}} - \frac{I_o}{n_d} + \frac{1}{n_d}\sum_d I_{o,a(d)} \times \frac{I_d - I_{c(o),d}}{I - I_{c(o)}}\end{aligned}$$

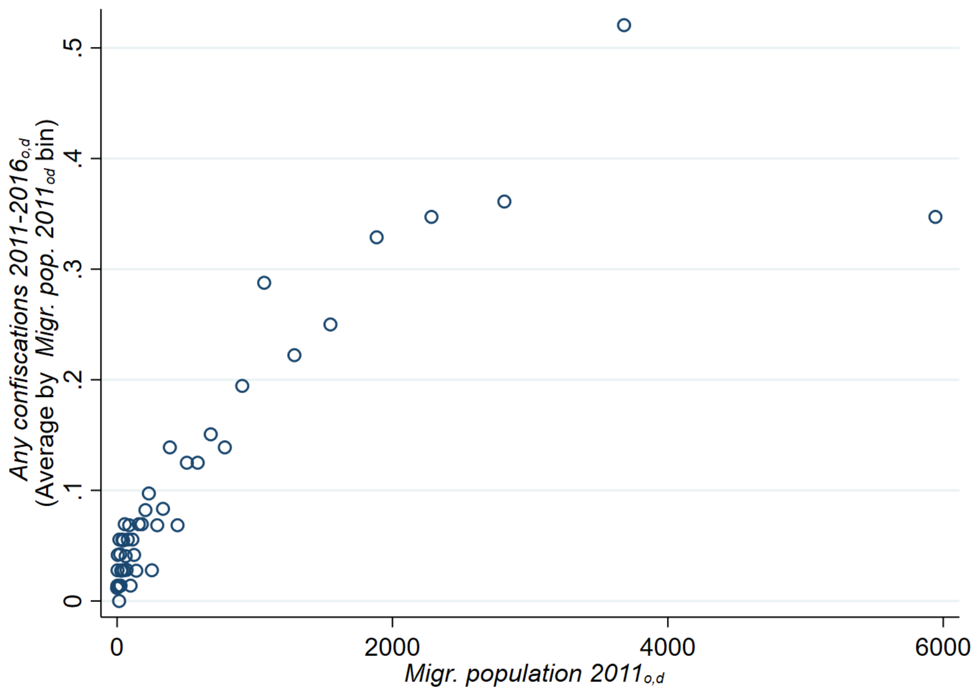
In my baseline estimation I use all 52 Spanish provinces and 102 countries, with an additional country group per continent. Therefore, any increase in the number of immigrant destinations $d$ or origins $o$ will not increase total immigration to Spain, $I^D$. Therefore the same aymptotic logic applies whereby a larger number of origin and destination regions lead to a larger proportion of the residual variation in the instrument to come from the push-pull interaction term, i.e., $\lim_{n_o \to \infty, n_d \to \infty} \hat{IV}_{o,d} = IV_{o,d}$.

# C Empirical Appendix

## C.1 Relaxing Functional Form Assumption

In my baseline gravity specification, equation 1, I measure the endogenous variable of interest as the log of one plus the number of immigrants measured in thousands: $\ln\left(1 + \frac{\#\ migrants_{o,d}^{2011}}{1000}\right)$. I motivate my choice of a log-functional form with the binscatter plot in Figure C.1 of the relationship between the immigrant population and the dummy variable for whether any confiscation occurs at the country-province level. To test whether my results are sensitive to changes in the function form of the endogenous variable, I perform two robustness exercises.

Figure C.1: Relationship between Import Confiscation Dummy and Immigrant Population




*Notes*: The figure shows the binscatter plot between the immigrant population in 2011 and a dummy variable for whether any import confiscation occurred between 2011 and 2016 at the country-province-pair level. For visual clarity, I drop the highest quantile, which in any case does not change the figure's log curvature.

First, I estimate my baseline specification across various alternative functional forms for the number of immigrants, as well as using a probit model. I show the results in Table C.1. Across functional forms, more immigrants tend to lead to more drug confiscations as I find in the baseline.

Table C.1: Robustness to Different Functional Forms

| | Any confiscation (2011–2016) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Import | Export | Import | Export | Import | Export |
| Log immigrant population (2001) | 0.203*** | 0.0920* | | | | |
| | (0.0607) | (0.0495) | | | | |
| $\ln\left(\frac{M_{o,d}^{2011}}{1000}\right)$ (-1 for $\infty$) | | | 0.118*** | 0.0362 | | |
| | | | (0.0282) | (0.0243) | | |
| $\left(M_{o,d}^{2011}\right)^{1/3}$ | | | | | 0.0224*** | 0.00946* |
| | | | | | (0.00774) | (0.00511) |
| Observations | 5564 | 5564 | 5564 | 5564 | 5564 | 5564 |
| Country FE | Y | Y | Y | Y | Y | Y |
| Province FE | Y | Y | Y | Y | Y | Y |
| Ln dist | Y | Y | Y | Y | Y | Y |
| 1st-stage F-statistic | 290.1 | 290.1 | 17.1 | 17.1 | 388.1 | 388.1 |

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

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

$$\begin{aligned}\mathbf{1}\left[C_{o,d}^{2011\text{–}2016} > 0\right] &= \alpha_o^{Import} + \alpha_d^{Import} + \beta^{Import} \ln(1 + \pi \times \#\ migrants_{o,d}^{2011}) + \delta^{Import} \ln(Dist_{o,d}) + \epsilon_{o,d}^{Import} \\ \mathbf{1}\left[C_{d,o}^{2011\text{–}2016} > 0\right] &= \alpha_o^{Export} + \alpha_d^{Export} + \beta^{Export} \ln(1 + \pi \times \#\ migrants_{o,d}^{2011}) + \delta^{Export} \ln(Dist_{o,d}) + \epsilon_{o,d}^{Export}\end{aligned} \tag{C.1}$$

with moment conditions

$$E\left[\boldsymbol{Z_{o,d}} \times (Y_{o,d} - \alpha_o - \alpha_d - \beta \ln(\pi \times \#\ migrants_{o,d}^{2011} + 1) - \delta \ln(Dist_{o,d})\right] = \mathbf{0} \tag{C.2}$$

$$E\left[\begin{pmatrix}\boldsymbol{\alpha_o} \\ \boldsymbol{\alpha_d}\end{pmatrix} \times (Y_{o,d} - \alpha_o - \alpha_d - \beta \ln(\pi \times \#\ migrants_{o,d}^{2011} + 1) - \delta \ln(Dist_{o,d}))\right] = \mathbf{0} \tag{C.3}$$

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

Table C.2 shows the results. My estimate of $\pi$ does not reject my baseline functional form assumption of $\pi = \frac{1}{1000}$ and rejects the more conventional functional form choice $\pi = 1$.[43] In addition, the estimates of $(\beta_1, \beta_2)$ also are statistically indistinguishable from my baseline coefficient estimates.

## C.2 Probit Estimation

In my baseline estimation, I use a linear probabiliy model. In Table C.3 I show the results of probit estimation. I estimate positive effects of immigrants on illegal imports and exports, though only the effect on imports is statistically significant.

[43] Note that my standard errors are not adjusted for the implicit constraint that $X > 0$ in $\ln(X)$ as suggested by Andrews (2002).

Table C.2: Effect of Immigrants on Drug Confiscations (GMM)

| | Drug Smuggling |
|---|---|
| $\beta^{Import}$ | 0.191*** |
| | (0.045) |
| $\pi$ | 0.017 |
| | (0.022) |
| $\beta^{Export}$ | 0.143*** |
| | (0.070) |
| Observations | 5564 |

*Notes*: The table presents coefficient estimates from nonlinear GMM estimation of moments C.2 and C.3. Standard error for $\pi$ not adjusted for the constraint that the log function does not accept nonpositive arguments. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.3: Probit Estimation of Gravity

| | Any confiscation (2011–2016) | |
|---|---|---|
| | (1) | (2) |
| | Import | Export |
| Log immigrants 2011 | 0.334** | 0.0362 |
| | (0.163) | (0.179) |
| Observations | 3224 | 2728 |
| Country FE | Y | Y |
| Province FE | Y | Y |
| Ln dist | Y | Y |
| 1st-stage F-statistic | 149.6 | 149.6 |

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

## C.3 Varying Instrumental Variables

I next test the degree to which my results are robust to different choices of instrumental variables. In Panel A of Table C.4, I re-estimate my baseline gravity specification (equation 1) using only the instrument for immigrant inflows in the 1990s (the first row) and the 2000s (the second row), where each cell refers to a separate regression. In addition, I estimate my baseline without the higher-order interaction terms between the instruments in the third row of Panel A. Across all these regressions, I find that the immigrant population induces an increase in both imports and exports of illegal drugs, although when I include only a single instrument my results are less precisely estimated.

Table C.4: Varying the Instrumental Variable

| PANEL A: Using subsets of instruments | Import confiscations (Dummy) | Export confiscations (Dummy) |
|---|---|---|
| Only immigration 1991–2001 | 0.151** | 0.09 |
| | (0.064) | (0.055) |
| Only immigration 2001–2011 | 0.086 | 0.073** |
| | (0.066) | (0.037) |
| Immigration 1991–2001, without squared and interaction terms | 0.112* | 0.08* |
| | (0.062) | (0.042) |
| **PANEL B: variations of leave-out categories** | **Import confiscations (Dummy)** | **Export confiscations (Dummy)** |
| Excluding origins with correlated 2011 immigrant pop.: $I^t_{o,-r(d)} \times (I^t_{-corr(o),d}/I^t_{-corr(o)})$ | 0.201*** | 0.09** |
| | (0.069) | (0.044) |
| Excluding provinces with correlated 2011 immigrant pop.: $I^t_{o,-corr(d)} \times (I^t_{-c(o),d}/I^t_{-c(o)})$ | 0.093*** | 0.09* |
| | (0.063) | (0.052) |
| Excluding provinces, origins with correlated 2011 immigrant pop.: $I^t_{o,-corr(d)} \times (I^t_{-corr(o),d}/I^t_{-corr(o)})$ | 0.344*** | 0.038 |
| | (0.121) | (0.061) |
| Excluding autonomous communities adjacent to the destination: $I^t_{o,-adj(d)} \times (I^t_{-c(o),d}/I^t_{-c(o)})$ | 0.168*** | 0.052 |
| | (0.043) | (0.036) |

*Notes:* The table presents coefficient estimates from instrumental variable regressions of equation 1, where each cell presents the coefficient on *Log immigrants* 2011 from seperate regressions. Panel A shows subsets of instruments relative to my baseline instrument set. Panel B shows alternative formulations of the baseline instrumental variable. In particular, I exclude from the pull factor countries with correlated immigrant populations across all Spanish provinces (in the first row of Panel B); from the push factor, provinces with correlated immigrant populations across all origins (second row); both correlated origins and provinces simultaneously excluded from the pull and push factors (third row); and finally excluding autonomous communities adjacent to province $d$'s autonomous community (last row). For a region to be excluded due to correlation, the correlation coefficient must be greater than 0.5 with a p-value lower than 0.05. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

A remaining concern in the identification strategy is that the leave-out categories do not adequately capture groups of countries or provinces that send or receive immigrants for similar reasons. For example, as discussed in Section 3.3, if Lebanon sends immigrants and drugs to Barcelona due to the similar Mediterranean climate, just like Morocco, then the confounding factor of a similar climate may still be driving my results, even when using the baseline instrument defined in equation 2. To address this concern, I leave out regions with correlated immigrant populations, shown in Panel B of Table C.4.[44]

In the first row of Panel B, I construct the pull component of the instrument leaving out countries that have immigrant populations that correlate with country $o$'s immigrant population (across Spain's 52 provinces). In particular, if this correlation coefficient rises above 0.5 with a p-value below 0.05, I drop it from the pull factor. Similarly, in the second row of Panel B, I exlcude from the push component provinces with immigrant populations that correlate with province $d$ across all origin countries. For both sets of instruments, my main result remains.

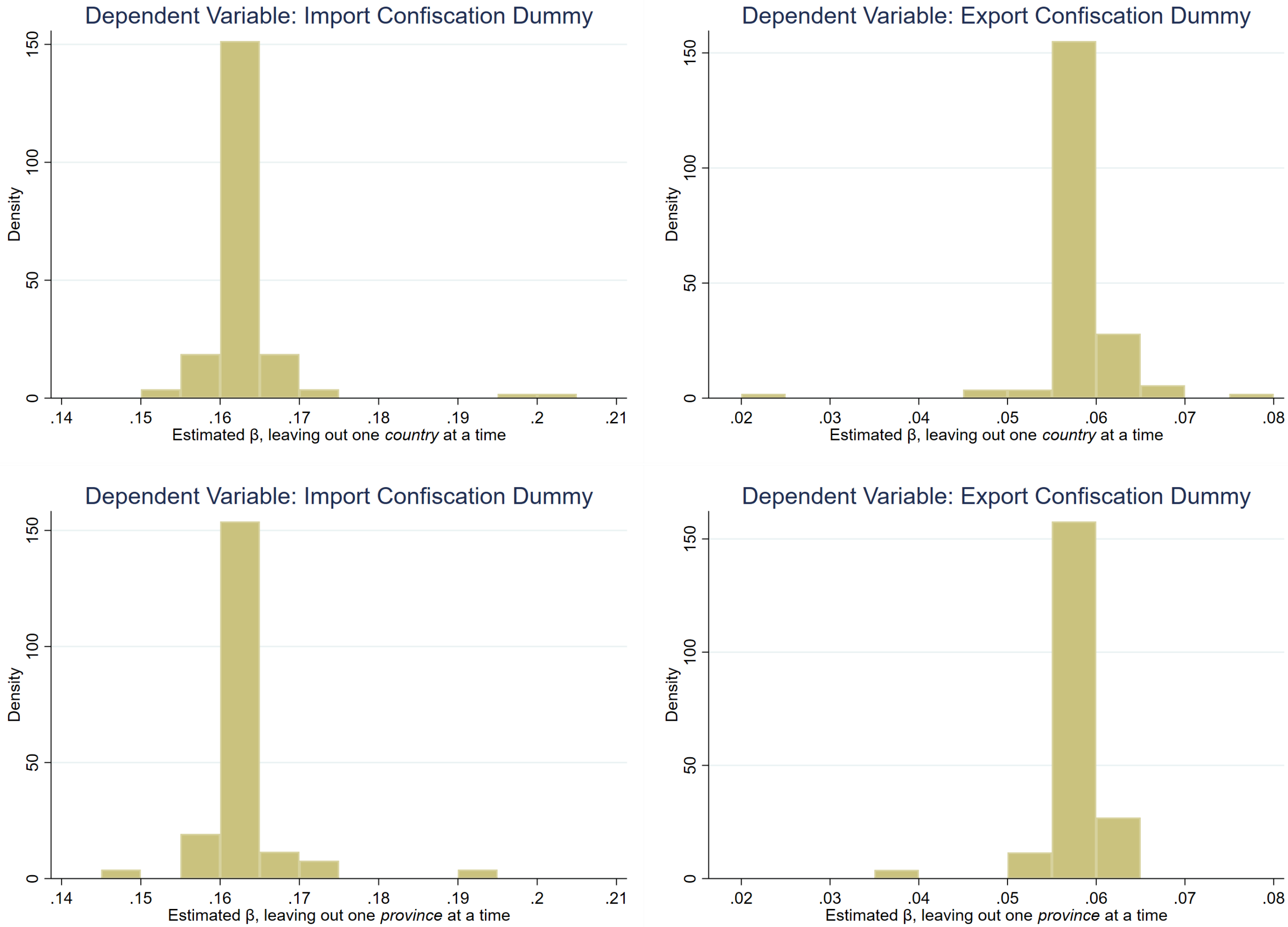
In the third row of Panel B, I simultaneously leave out correlated provinces from the push factor and correlated origins from the pull factor. In the final row of Panel B, I remove all autonomous communities adjacent to the autonomous community of province $d$ in addition to $d$'s own autonomous community. For both sets of instrumental variables the coefficient on the immigrant population's effect on import confiscations remains large and statistically significant, while for export confiscations the coefficient falls and is less precisely estimated. Overall the pattern shown in Panel B is that the effect of immigrants on imports and exports of illegal drugs remains positive, albeit sometimes imprecisely estimated for exports.

## C.4 Varying Estimation Sample

Drug trafficking into Spain is primarily driven by a select few countries—Morocco, for example, is the dominant exporter of cannabis to Spain. To see whether any single country or province drives my baseline results, I re-estimate my baseline gravity specification separately leaving out each province and each country, for a total of 159 regressions. Figure C.2 shows the distribution of $\beta$ estimates from equation 1 when dropping a single country per regression (top row) or a single province (bottom row), with imports on the left and exports on the right. I estimate a positive $\beta$ regardless of which region I drop from the sample, suggesting that no single country or province drives my baseline results.

[44] These exercises follow Table 5 of Burchardi et al. (2019).

Figure C.2: Effect of Immigrants on Drug Trafficking: Dropping Countries, Provinces One at a Time

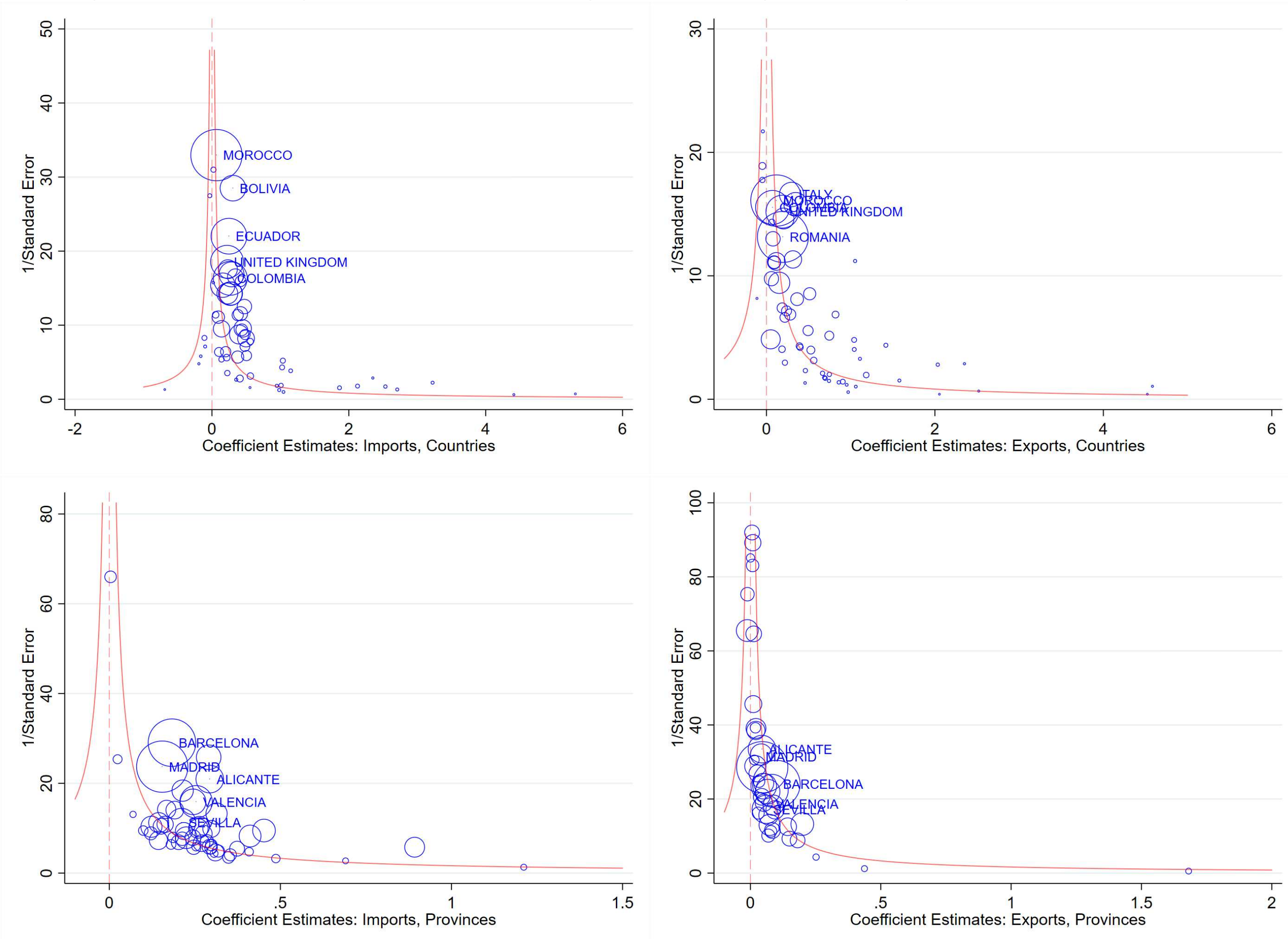



*Notes*: The figures show the distribution of the estimated effect of immigrants on illegal drug confiscations ($\beta$ from equation 1) when leaving out one nationality (in the top row) or province (bottom row) for each regression. The figures show the distribution of $\beta$s when the dependent variable of equation 1 is a dummy for whether any drug trafficking (imports on the left and exports on the right) with a given origin country was confiscated locally between 2011 and 2016.

Moreover, the maximal standard error for the excluded countty import regressions (top left) is 0.049, meaning all estimated coefficients are statistically significant as well. For exports (top right), only about half of coefficients are statistically significant. Similarly for leaving out one province at a time (bottom row), import coefficients are always statistically significant while export coefficients are statistically significant only for about half of province leave-outs.

I also explore the heterogeneity of the effect of immigrants on drug trafficking across individual countries and Spanish provinces. In Figure C.3, I plot coefficients on the immigrant population's effect on imports (left column) and exports (right column) across provinces (bottom) and countries (top). The red curve displays the threshold for statistical significance at the 10% level, with circle size corresponding to province population or nationality population. I find that nearly all individual provinces and countries exhibit a positive effect of immigrants on illegal trafficking, with most coefficients being statistically significant. However, given that each province regression is identified from 107 observations and each country regression from 52 observations, it is unsurprising that some estimates are statistically insignificant.

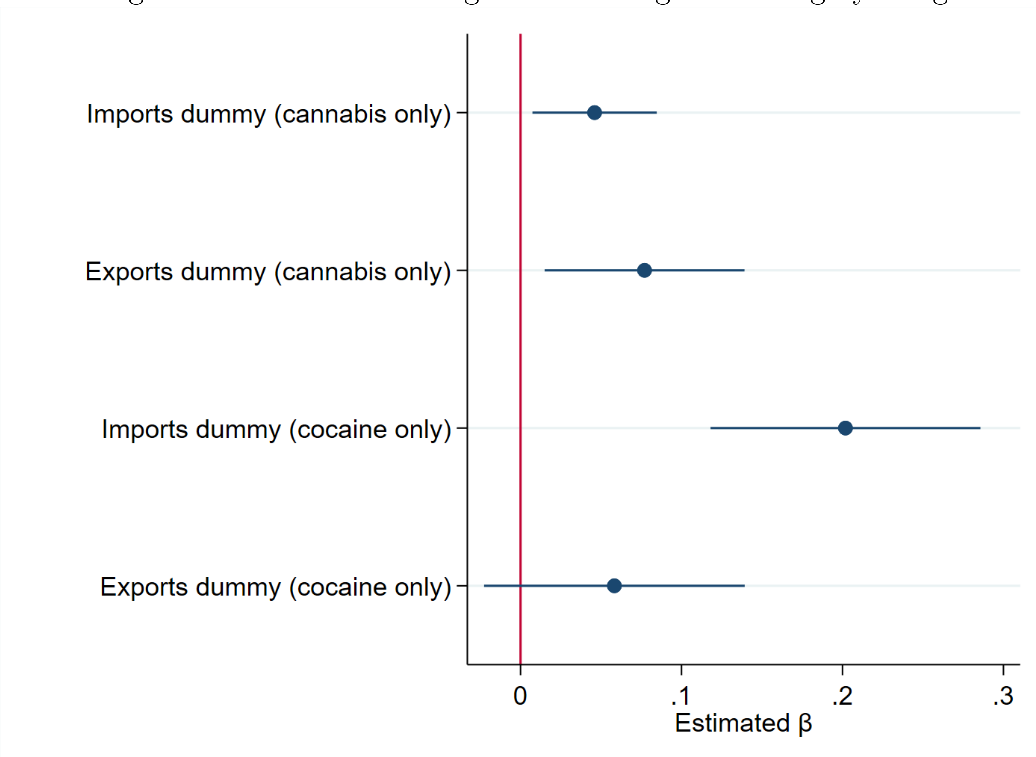
Figure C.3: Heterogeneous Effect of Immigrants on Drug Trafficking by Country and Province




*Notes*: This figures shows funnel plots of the estimated coefficients and inverse standard errors from 2SLS regressions of drug trafficking dummies (imports in top charts; exports in bottom charts) on *Log migrants* 2011, controlling for log distance between the immigrants' origin country and Spanish province, and estimated separately for each individual Spanish province and origin country. Circle sizes represent the province population (left-hand charts) or the number of immigrants in Spain from the origin country (right-hand charts). Labeled countries/provinces are the top 5 largest by population in Spain. The x-axis is the coefficient estimate, and the y-axis is the inverse of the standard error of that estimate. The curve plots $y = \pm 1.65/x$; hence, circles above this curve are statistically significant at the 10% level. I separately drop countries or provinces for which I observe no import or export confiscations. For readability, I drop China in the top right chart and Ukraine in the bottom right chart, which are both major outliers, though both coefficients are statistically indistinguishable from zero.

Finally, I estimate the immigrant-confiscations relationship separately by the two major drugs trafficked in Spain: cannabis and cocaine, as shown in Figure C.4. I estimate positive and statistically significant effect sizes for both imports and exports across both drugs. Cocaine imports are more significantly raised by immigrants than cannabis, consistent with the fact that cocaine must be imported, whereas cannabis may be produced locally in Spain.

Figure C.4: Effect of Immigrants on Drug Trafficking by Drug




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

## C.5 Standard Errors

In my baseline specification, I cluster standard errors at the country level. To test whether my results are robust to alternative standard error clustering, including two-way clustering, I re-estimate my baseline specification using various different clustering geographies. Table C.5 shows these estimates, which remain statistically significant across the different clustering geographies for imports and exports. Moreover, the clustering geography used in my baseline estimation, country-level, produces the largest standard errors.

Table C.5: Gravity Specification: Alternative Standard Errors

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

*Notes:* The table presents coefficient estimates and various standard errors from IV regressions of equation 1 at the country-province level. I control for nationality and province fixed effects as well as log distance. *Log immigrants 2011* is instrumented with the leave-out push-pull IV from equation 2. I cluster by country in my baseline specification.

## C.6 Panel Estimation

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

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

$$Y_{o,d}^t = \alpha_o^t + \alpha_d^t + \beta M_{o,d}^t + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d}^t \tag{C.4}$$

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

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

$$Y_{o,d}^t = \alpha_o^t + \alpha_d^t + \beta M_{o,d}^t + \alpha_{o,d} + \varepsilon_{o,d}^t \tag{C.5}$$

These fixed effects absorb time-invariant bilateral characteristics, such as climatic or geographic similarity. However, the bilateral fixed effects $\alpha_{o,d}$ change the interpretation of $\beta$. In particular, $\beta$ represents the change in illegal drug trafficking resulting from year-to-year net changes in the immigrant population. Therefore, equation C.5 sheds light on the effect of recent immigrants on illegal trafficking, but it does not test whether long-run migrant networks shape illegal trafficking.

To achieve causal identification, I use the instrumental defined in equation 2 for the decade 1991–2001 when estimating equation C.4:

$$IV_{o,d}^{1991\text{–}2001} = I_{o,-a(d)}^{1991\text{–}2001} \times \frac{I_{-c(o),d}^{1991\text{–}2001}}{I_{-c(o)}^{1991\text{–}2001}} \tag{C.6}$$

In addition, I include a time-varying instrument that predicts bilateral immigrant inflows between 2001 and year $t$ when estimating both equations C.4 and C.5,

$$IV_{o,d}^{t} = I_{o,-a(d)}^{2001\text{–}t} \times \frac{I_{-c(o),d}^{2001\text{–}t}}{I_{-c(o)}^{2001\text{–}t}} \tag{C.7}$$

I compute immigrant inflows between 2001 and $t$ as the net change in the bilateral immigrant population as measured in the population registry. Consistent with my baseline specification, I include interaction and squared terms when estimating the first-stage. I estimate equations C.4 and C.5 for the years 2006 through 2016.

As shown in Table C.6, I find that immigrants raise imports and exports, consistent with my baseline results. For imports, a 10% increase in the population of immigrants from country $o$ raises the likelihood of import confiscations by 1 percentage point[45] without $o, d$ fixed effects or by 2.1 percentage points when including $o, d$ fixed effects. For exports, a 10% increase in immigrants from $o$ raises the likelihood of illegal drug exports to $o$ by 0.3 percentage points (without the bilateral fixed effect $\alpha_{o,d}$). When controlling for the bilateral fixed effect, the effect of immigrants on exports of illegal drugs is statistically indistinguishable from 0.

[45] Using $\hat{\beta} = 0.185$ from column 1 in Table C.6 and the average country-province-pair immigrant population of 1229, I compute: $\mathbb{1}\left[C_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 1229\right] = 0.189 \left(\ln\left(1 + \frac{1229\times 1.1}{1000}\right) - \ln\left(1 + \frac{1229}{1000}\right)\right) \approx 0.0101$.

Table C.6: Effect of Immigrants on Drug Trafficking: Panel Analysis

| | Drug Confiscations Dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Imports | Imports | Exports | Exports |
| Log immigrant population | 0.189*** | 0.391** | 0.0473*** | -0.0641 |
| | (0.0138) | (0.176) | (0.00876) | (0.159) |
| Observations | 58916 | 58916 | 58916 | 58916 |
| Log distance | Y | Y | Y | Y |
| Country-Year FE | Y | Y | Y | Y |
| Province-Year FE | Y | Y | Y | Y |
| Origin-Province FE | N | Y | N | Y |
| 1st-stage F-statistic | 525.2 | 34.7 | 525.2 | 34.7 |

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

## C.7 Legal Trade

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

As in Section 3.7, I take a control function pseudo-Poisson maximum likelihood estimation approach. I show the results in Table C.7. Consistent with Burchardi et al. (2019), I find no statistically significant effect of immigrants on legal imports (column 1) or exports (column 2). One potential explanation for the discrepancy between the effect of immigrants on legal versus illegal trade is that with illegal trade, immigrants have to rely even more on informal social ties than with legal trade. Legal institutions exist to facilitate the flow of legal trade, thus offsetting some of the need for informal ties.

Table C.7: Effect of Immigrants on Legal Trade

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

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

# D Additional Tables and Figures

Table D.1: Effect of Immigrants on Drug Trafficking (OLS, Adding Fixed Effects)

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

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

Table D.2: Effect of Immigrants on Drug Trafficking Heterogeneity

PANEL A: HETEROGENEITY BY DRUG HUBNESS AND PRODUCTION COUNTRIES

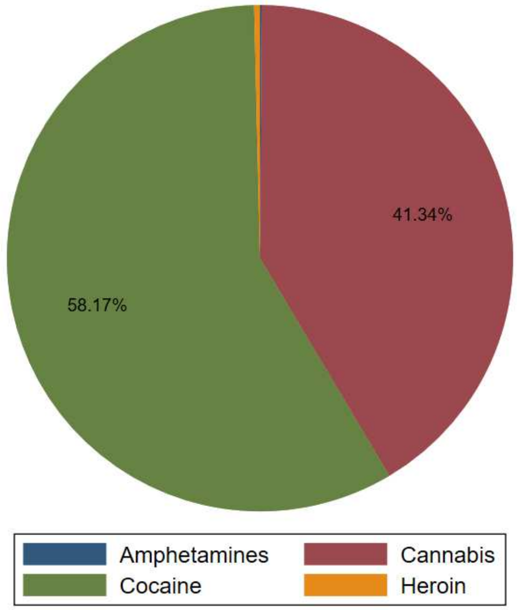
| | Outcome: Drug Confiscations Dummy | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Imports | Exports | Imports | Exports | Imports (cocaine) | Imports (cannabis) |
| Log immigrants 2011 | 0.126** | 0.0528 | 0.674*** | 0.245*** | | |
| | (0.0543) | (0.0389) | (0.205) | (0.0844) | | |
| Log immigrants 2011 × % of seized drugs from $o$ | 1.377*** | -0.192 | | | | |
| | (0.299) | (0.159) | | | | |
| Log immigrants 2011 × Drug hubness rank | | | -0.00138*** | -0.000409** | | |
| | | | (0.000338) | (0.000168) | | |
| Cocaine Producer$_o$=0 × Log immigrants 2011 | | | | | 0.181*** | 0.0466** |
| | | | | | (0.0480) | (0.0219) |
| Cocaine Producer$_o$=1 × Log immigrants 2011 | | | | | 0.281*** | 0.0360 |
| | | | | | (0.0247) | (0.0277) |
| Observations | 5564 | 5564 | 5564 | 5564 | 5564 | 5564 |

PANEL B: BY MODE OF TRANSPORT

| | Outcome: Drug Confiscations Dummy | | | | | |
|---|---|---|---|---|---|---|
| | Imports (air) | Exports (air) | Imports (land) | Exports (land) | Imports (sea) | Exports (sea) |
| Log immigrants 2011 | 0.231*** | 0.0402 | 0.0650** | 0.0407* | 0.143*** | 0.0296 |
| | (0.0517) | (0.0359) | (0.0281) | (0.0208) | (0.0518) | (0.0196) |
| Observations | 5564 | 5564 | 5564 | 5564 | 5564 | 5564 |

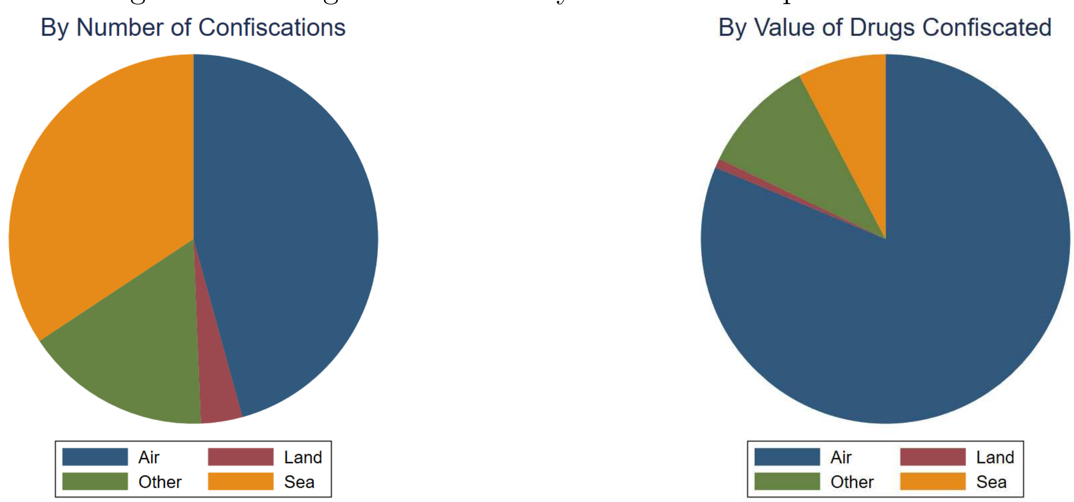
*Notes:* The table presents instrumental variable regression estimates at the country-province level. The dependent variable is a dummy for whether any illegal drugs trafficked with country $o$ were confiscated in province $d$ between 2011 and 2016, separately for imports and exports. In columns 1–4 of Panel A, I modify equation 1 to include a term interacting *Log immigrants 2011* with a measure of the immigrants' origin country drug-hubness, either the fraction of confiscated drugs worldwide originating in the country or the ordinal rank of that fraction. I instrument for *Log immigrants 2011* using the IV defined in equation 2, the IVs interacted across decades and squared, and that set of IVs interacted with the drug hubness measure. In columns 5 and 6 of Panel A, I add to equation 1 a term interacting the immigrant population with a dummy for whether the immigrants' origin is a major cocaine producing country (either Bolivia, Colombia, or Peru). In Panel B, I show the effect of immigrants on drug trafficking separately by the mode of transportation for the confiscated drugs: either by air, land, or sea. All regressions control for country and province fixed effects as well as log distance. Standard errors are clustered at the country-level in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure D.1: Confiscations by Drug Type



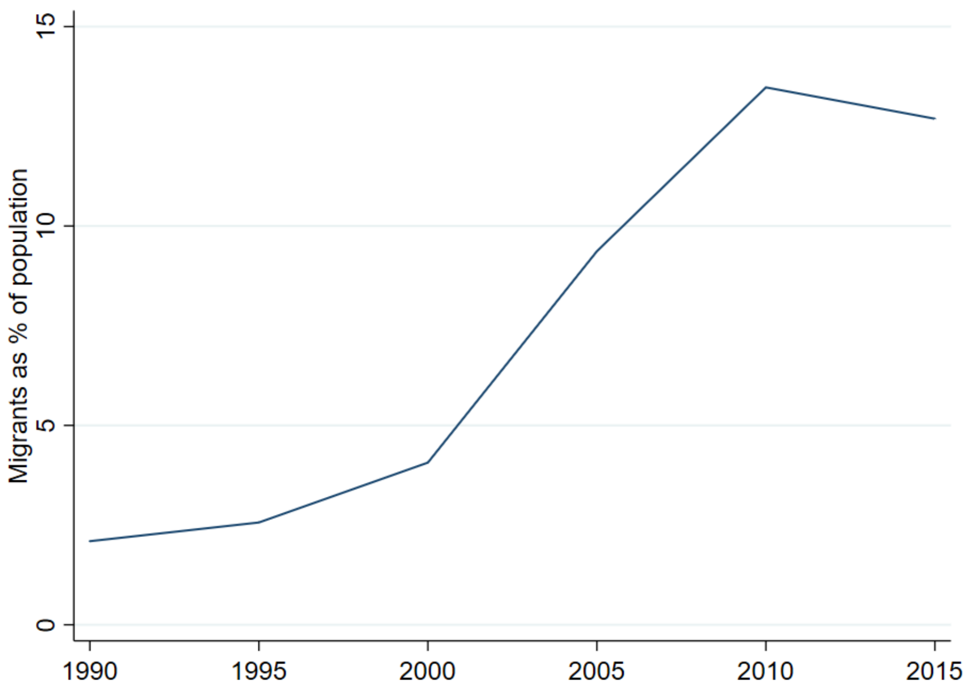

*Notes*: This figure shows the makeup of drug confiscations in Spain by drug type. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the United Nations Office of Drugs and Crime (UNODC).

Figure D.2: Drug Confiscations by Mode of Transport



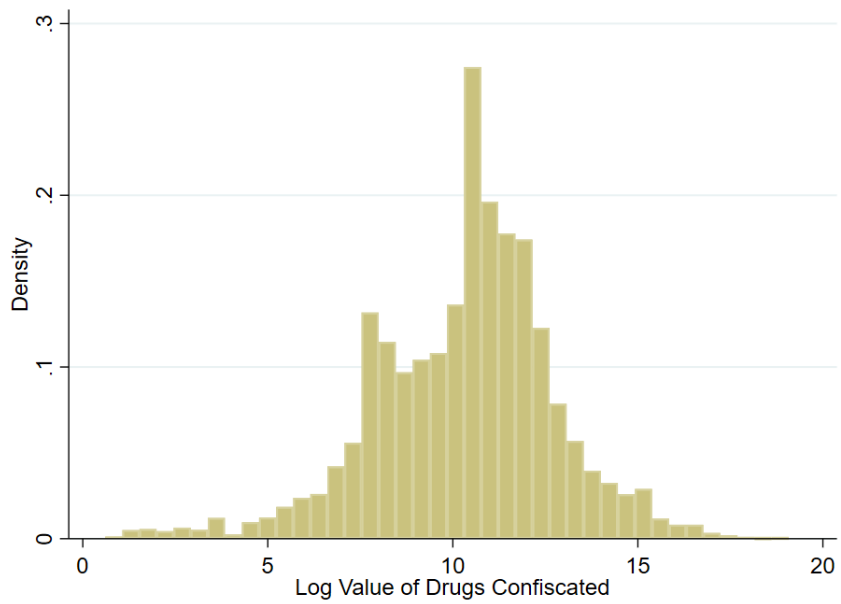

*Notes*: The figure shows the shares of mode of transportation of confiscated drugs. On the left I plot fraction of confiscation events, on the right, I plot the share of dollar values confiscated. Data come from the United Nations Office of Drugs and Crime.

Figure D.3: Immigrant Population Share in Spain, 1990–2015



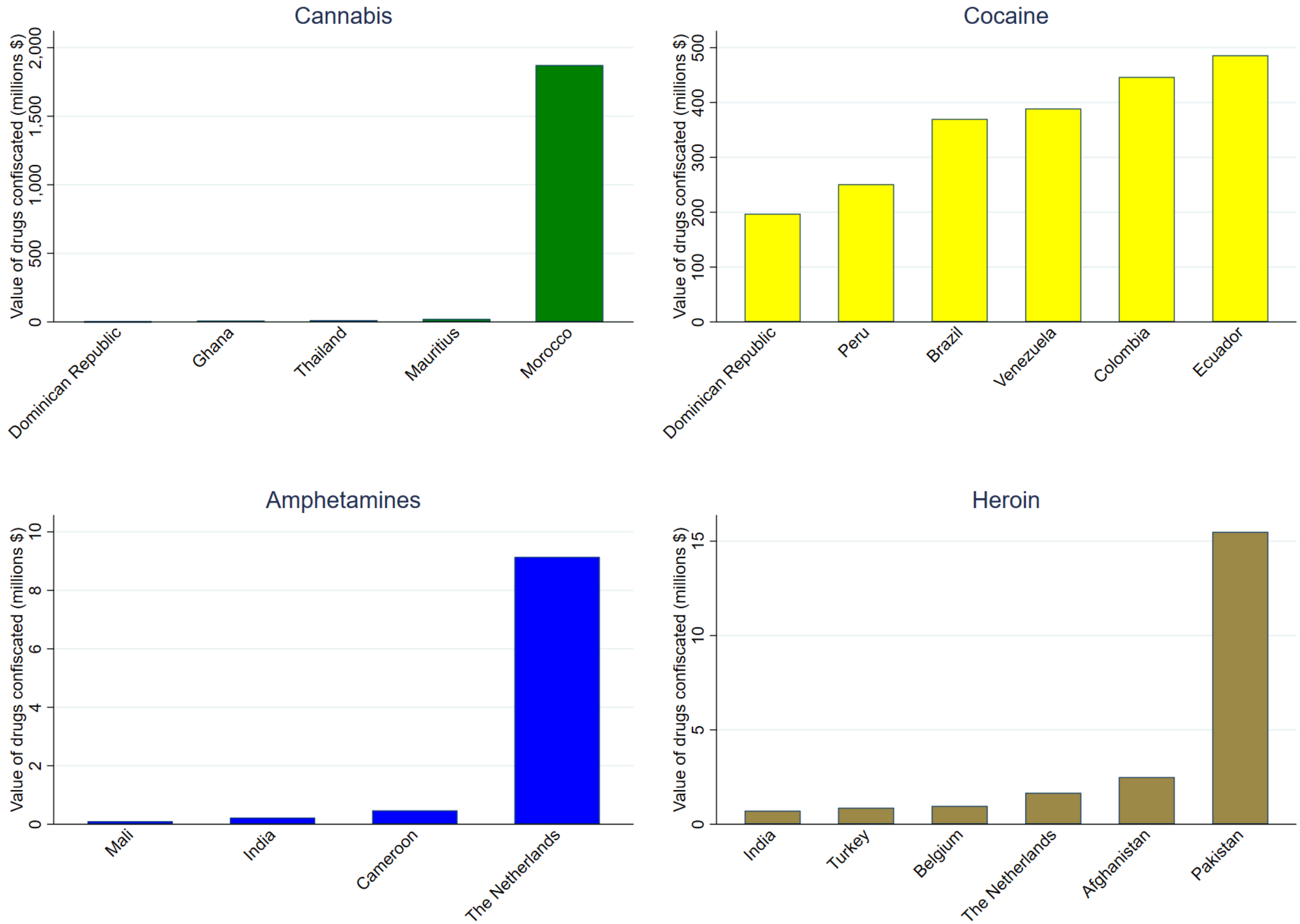

*Notes*: This figure shows the fraction of the Spanish population born in another country over time. The data are reported by the World Bank but originally come from the United Nations Population Division.

Figure D.4: Distribution of Log Value of Confiscations



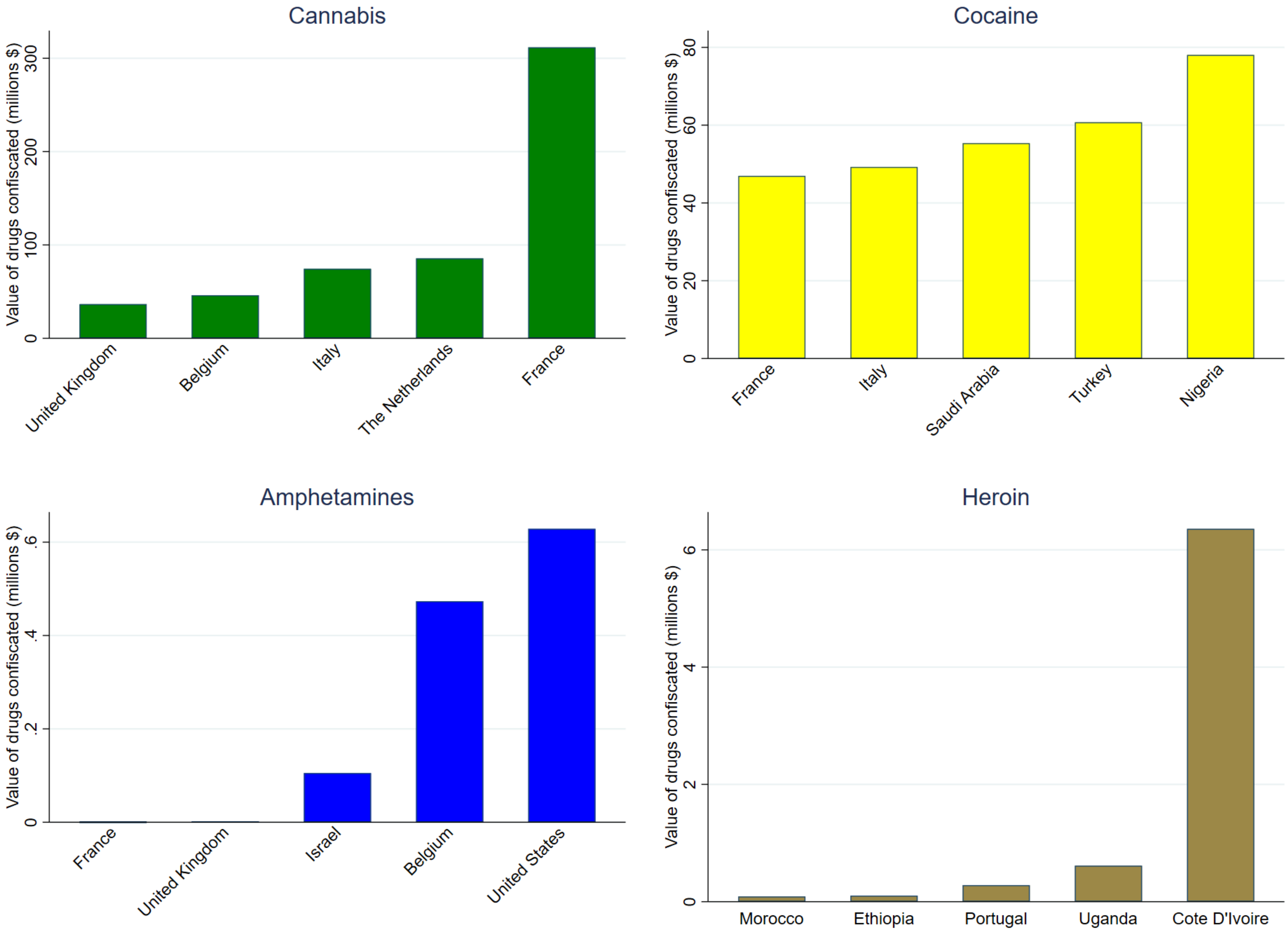

*Notes*: This figure shows the distribution of the log value of drug confiscations in Spain between 2011 and 2016 as reported to the United Nations Office of Drugs and Crime (UNODC). Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure D.5: Top Five Origins by Drug



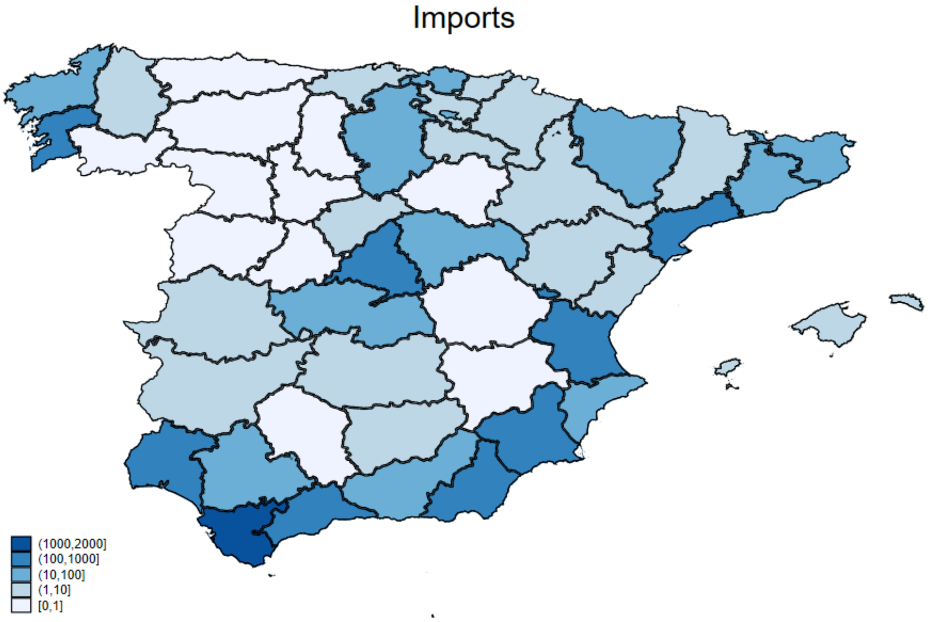

*Notes*: This figure shows the top five countries of origin of illegal drugs confiscated in Spain between 2011 and 2016 by drug. Data come from the United Nations Office of Drugs and Crime.

Figure D.6: Top 5 Intended Destinations by Drug



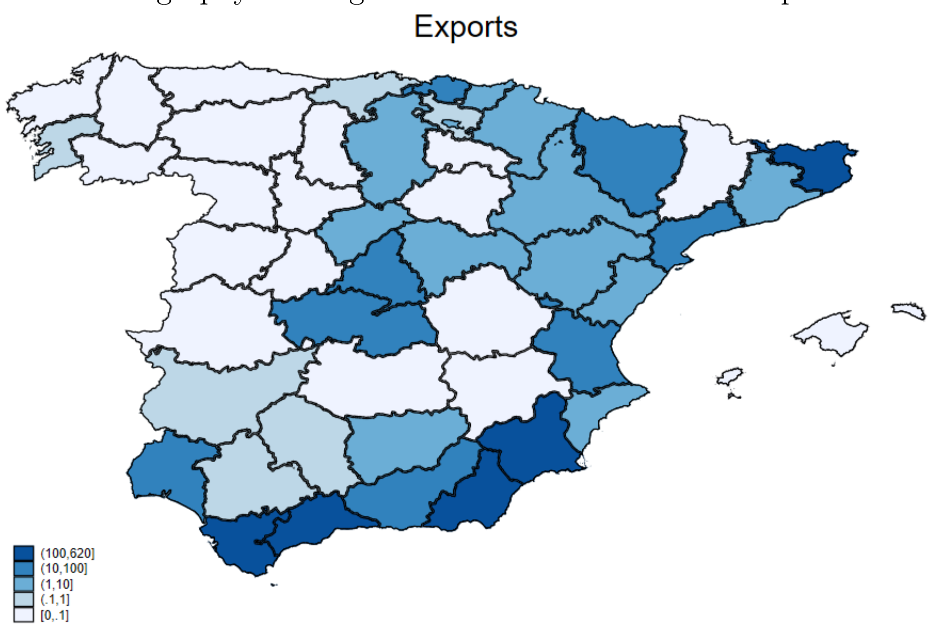

*Notes*: This figures shows the top five countries of intended destination of illegal drugs confiscated in Spain between 2011 and 2016. Data come from the United Nations Office of Drugs and Crime.

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



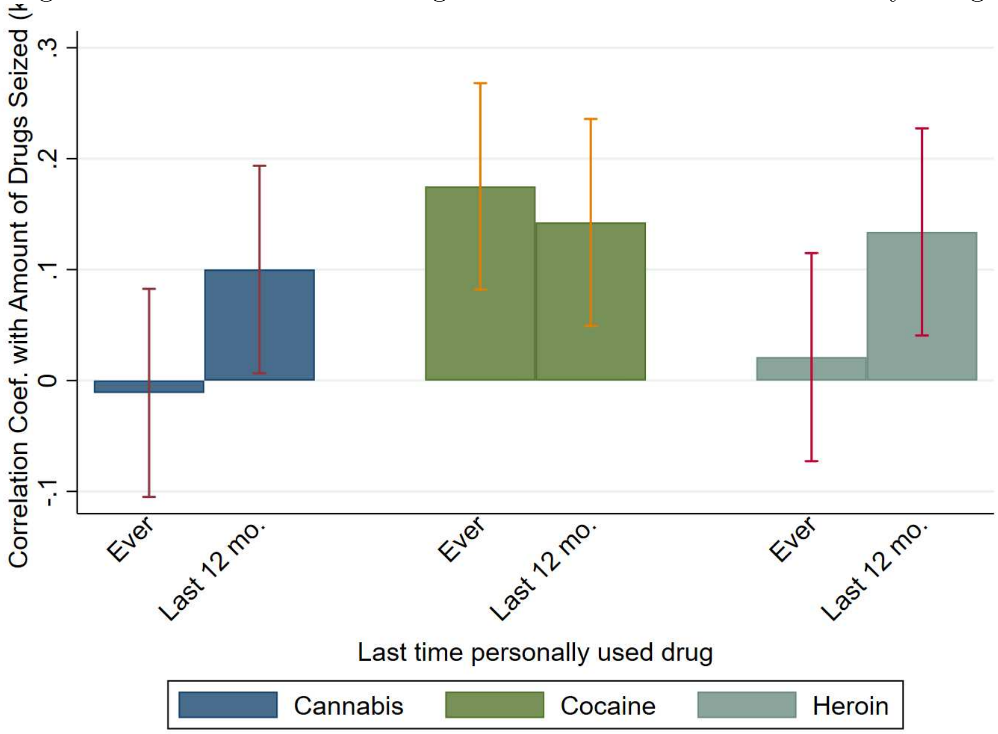

*Notes*: This figure shows the distribution of drug confiscations of imports (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office of Drugs and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

Figure D.8: Geography of Drug Confiscations Intended for Export from Spain



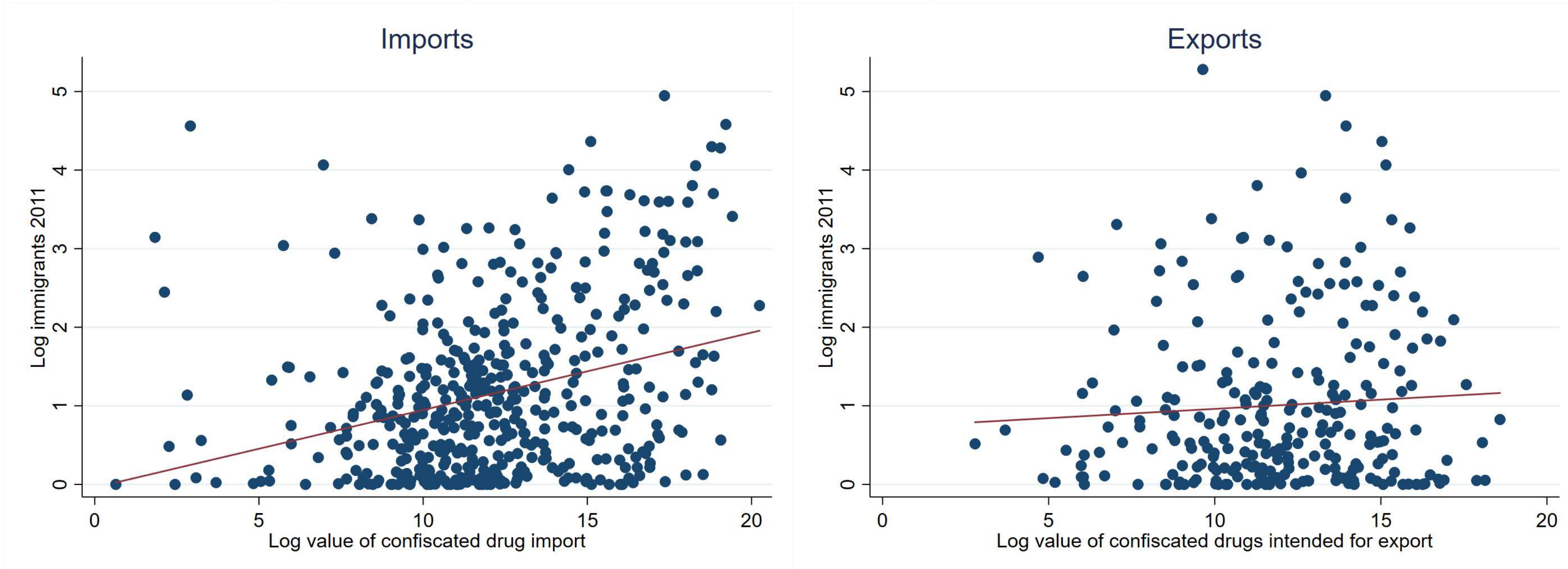

*Notes*: This figure shows the distribution of confiscations of drugs intended for export (measured in dollars by the estimated wholesale value of confiscated drugs) per capita across Spanish provinces for confiscations occurring between 2011 and 2016 as reported by Spain to the United Nations Office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

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




*Notes*: This figure shows the correlation coefficient between the amount confiscated per capita for each drug with the fraction of respondents in a province who report having ever used the drug or having used the drug within the last 12 months. Amphetamines were not asked about until the 2013 survey and are thus excluded. Ninety percent confidence intervals are shown. Correlations are estimated on a cross-section of 52 Spanish provinces, averaged across 2011 to 2016 for drug confiscations and across the 2011, 2013, and 2015 waves of the EDADES (Survey on Alcohol and Drugs in Spain).

Figure D.10: Drug Confiscations and Number of Immigrants Unconditional Correlation

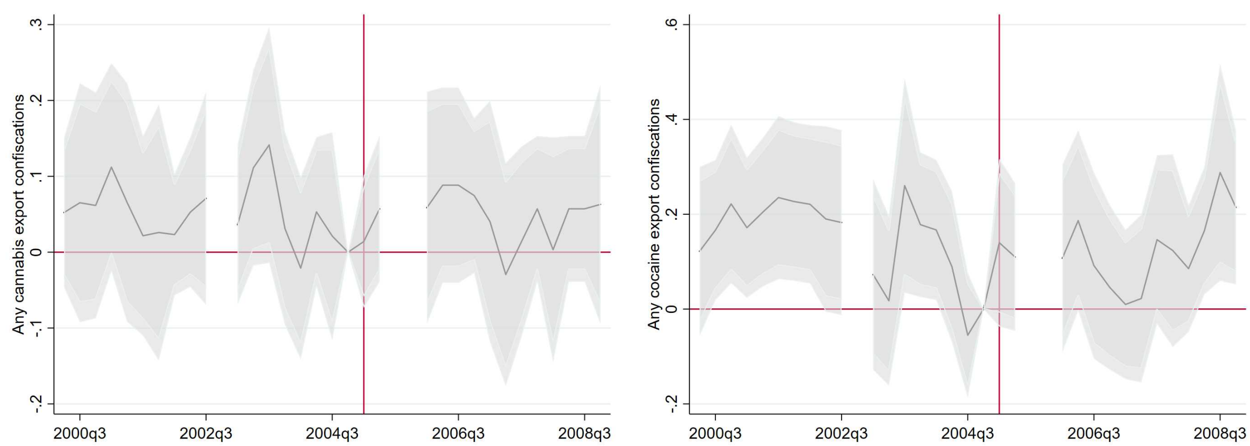



*Notes*: The figure on the left shows the scatter plot of the bilateral log value of confiscated drug imports on the x-axis with the bilateral log number of immigrants measured in 2011 on the y-axis. The figure on the right is the same but plots the log of the value of drugs confiscated intended for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

Figure D.11: Immigrant Work Permit Issuance

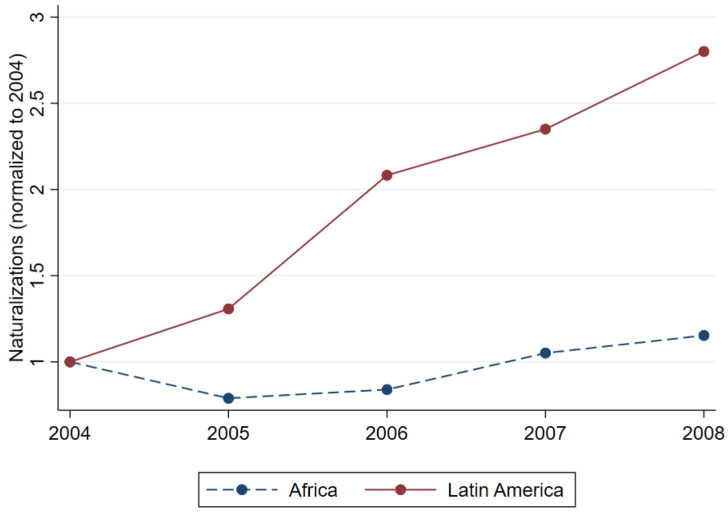

*Notes*: The figure showsthe number of residency permits granted to immigrants over time in Spain. Data come from Spain's Ministerio de Empleo y Seguridad Social.

Figure D.12: Effect of 2005 Immigrant Legalization on Illegal Drug Exports




*Notes*: The figure shows event study plots of the effect of the 2005 immigrant regularization on export confiscations of cannabis (on the left) and cocaine (on the right). The dependent variable is whether any drugs were confiscated intended to go to the origin country in that quarter. Plot is estimated using equation 12. The dark grey area shows the 90% confidence interval while the light grey area shows the 95% confidence interval.

Figure D.13: Immigrant Citizenship Acquisition by Continent




*Notes*: The figure shows the number of immigrants obtaining citizenship, for both African immigrants (dashed blue line) and Latin American immigrants (solid red line). Data come from Spain's Ministerio de Empleo y Seguridad Social.