Migration and Drug Trafficking*

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Abstract

Does globalization also integrate illegal markets? Nearly $2 trillion per year is generated by illicit smuggling across international borders, yet little is known about what forces shape this trade. In this paper, I use novel data on nearly 10,000 seizures of illegal drugs in Spain to study how migrants affect the flow of illegal drugs. I first validate that seizures are a useful proxy for true drug imports using measures of drug availability by province. I exploit variation across Spanish provinces in the number of migrants by origin country to estimate how bilateral migration affects the likelihood and total value of drug seizures originating from the origin country while instrumenting for the number of migrants. I find that 10% more migrants raises the likelihood of a drug seizure occuring by 0.5 percentage points and the value of drugs seized by 12% on a bilateral link. I present evidence that this effect is driven by migrants without legal status and not variation in enforcement intensity.

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1 Introduction

Transnational crime, or the shipment of illegal goods across international borders, generates nearly $2 trillion per year in revenue (Mavrellis, 2017), amounting to almost 10% of world merchandise trade or 3% of world GDP. Much of this illegal trade generates negative externalities such as violence, and the consumption of such illicit goods may have negative consequences on individual health and productivity, as is the case with illegal drugs (NDIC, 2011). Despite the magnitude of illegal smuggling and its social consequences, little is known about what factors shape it.

This absence of evidence has not prevented politicians from speculating on the causes of illegal trafficking to their political advantage. For example, Donald Trump famously suggested that Mexican immigrants were "bringing drugs [and] crime" into the United States.[1] Such thinking without rigorous evidence may lead to suboptimal immigration policies if the underlying mechanisms relating migration to illegal trafficking are not well understood.

In this paper, I explore whether migration affects transnational drug trafficking and if so to what extent and through which mechanisms. There exist no causal estimates on the migration-drug trafficking relationship for two reasons. First, there is a notable lack of data on drug trafficking, an illegal and therefore hard-to-observe activity. While data on illegal drug activity in a particular location may exist, since immigrants may affect the wages and productivity of that location, identifying the separate mechanism at such aggregation is extremely challenging. Second, migration and drug trafficking may be endogenous. Without credible exogenous variation in migrant networks, it is difficult to rule out whether some unobserved factor is driving both migration and smuggling.

To address endogeneity concerns, I relate drug trafficking to the number of migrants at the *bilateral* level. Importantly, I can attribute my results to the effects that migrants have on reducing trade costs due to the bilateral nature of my baseline analysis (Felbermayr et al., 2015)[2], whereas a local-level regression of drug activity on the total number of migrants (from all origins)–similar to the standard analysis of the effect of immigration on crime–would conflate the effects of immigrants on local wages and productivity with their effects on trade costs. In addition, the bilateral level analysis allows me to control for origin and

[1] Other politicians have made similar points. For example, in 2017 then-presidential candidate Sebastian Pinera blamed Chile's immigration laws for "importing problems like delinquency, drug trafficking and organized crime." (Esposito and Iturrieta, 2017) The EU's High Representative for Common Foreign and Security Policy argued in 2003 that "Massive flow 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)

[2] Where I assume that drug types are not differentiable across trafficking origins, an assumption I justify later in the text.

destination fixed effects, which include regional economic and institutional development as well as multilateral resistance terms, among others. Since I use within-destination-country variation, origin fixed effects also control for national-level drug, visa, and foreign policies vis-a-vis the origin country.

Nevertheless, there may still be unobserved bilateral factors, such as geographic or climatic similarity, which affects both migration and smuggling. Consider the origin country of Morocco and the Spanish province of Alicante. Both border the Mediterranean Sea and thus share some geographic and climatic features. If Moroccan migrants have a preference for such features and traffickers from Morocco are more comfortable navigating the Mediterranean Sea and climate, then migration and drug trafficking may be determined by these outside factors. To overcome such confounders, I adapt the leave-out push-pull instrument recently developed by Burchardi et al. (2019) to my context. This instrument interacts the relative attractiveness of immigrant destinations–the pull factor–with the arrival of migrants from different origins–the push factor. For example, if many immigrants are arriving in Spain from Morocco in a particular decade, and many immigrants from other continents are settling in Alicante in that decade, then the instrument will predict many Moroccans to flow into Alicante in that decade.

To make progress on the lack of data, I use a novel data set of international drug seizures at the bilateral level compiled by the United Nations Office of Drugs and Crime (UNODC). These data are unique in that they report the country from which drugs were trafficked, a field typically missing in data sets used to study illegal drug markets. I first validate these data as a proxy for actual flows of illegal drugs by correlating local seizures with survey-based measures of local drug availability. I find that more seizures predict greater availability of illicit drugs. Finally, the data report the location *within-country* of the drug seizure, allowing me to exploit variation at the sub-national level.

Spain is the ideal context to study the relationship between migration and drug trafficking. First, Spain reports exceptionally high-quality data on drug trafficking to the UNODC. Spain is also an important crossroads of global drug trafficking, in particular as the gateway for much of the cocaine and cannabis going to the European market. On migration, Spain has experienced substantial immigration in the past several decades, with the share of the population born abroad rising from less than 1% in 1991 to over 10% in 2011. Finally, Spain has superior measurement of the number of irregular migrants (i.e. those without legal status) relative to other developed countries. I consider the period of 2011 to 2016 and exploit cross-sectional variation among Spain's 52 provinces and a set of 102 origin countries for which I observe bilateral migrant stocks.

My baseline results show that migration matters for the flow of illegal drugs. I find that a 10% increase in the size of the bilateral migrant network raises the likelihood of a seizure occurring by 0.5 percentage points and the value of bilateral drugs seized by 12%, a magnitude comparable to estimates of the effect of migrant networks on legal trade. These effects are robust to choices on functional form and samples.

Several mechanisms may be driving my results: (1) enforcement intensity, which drives the selection of drug flows into observable data, may be shaped by migration, (2) migrants may prefer illegal drugs from their home countries, (3) trade in drugs may be diverted to from low-migration bilateral links to high-migration bilateral links, but overall imports may not rise, (4) the composition of migrants in terms of human capital and cultural characteristics which may also affect entry into drug trafficking, and (5) policies which inhibit integration of migrants into the labor market.

I rule out that the first three mechanisms (enforcement intensity, migrant preferences for illegal drugs, and trade diversion) drive my results.

I rule out that variation in enforcement intensity across bilateral links drives my results. First, I demonstrate that the estimated elasticity of migration with respect to seizures is equivalent to the elasticity of migration and actual drug flows for bilateral links at the extensive margin of trafficking. I find that my baseline results do not differ statistically when subsetting for bilateral links predicted to be at the extensive margin. Second, I show that at the Spanish province level, more migrants lead to more drug consumption, suggesting that more drugs are in fact being imported when more migrants are present. Finally, I quantitatively rule out that changes in enforcement intensity in response to migration could explain my baseline effect size.

Migrant preferences are unlikely to drive my results for two reasons. First, migrants consume drugs at about half the rate of the native-born. Second, illegal drugs are mostly homogenous across trafficking origins (though not necessarily production origin). To assess the importance of trade diversion in explaining my results, I estimate a specification at the province level. I find that a 10% increase in the proportion of migrants in the local population in a province raises seizures of drugs imported into the province by 14%. This suggests that net of trade diversion, migrants still raise overall illegal drug imports.

Finally, I find that migrant legal status is an important factor explaining the migrant-trafficking nexus. I find that increases in legal migration have no effect on drug seizures but that increases in irregular migration have a large and positive effect. This suggests that the composition of migrants (e.g. legal status correlates to underlying characteristics of migrants that drive their selection into drug trafficking employment) and policies limiting migrant access to the legal labor market play a role. To better understand to what extent policy shapes the relationship, I use an extraordinary regularization program of nearly half a million migrants to Spain in 2005. I find suggestive evidence that legalizing migrants' status reduces drug trafficking.

This paper relates to several literatures. Research in criminology on the determinants of international drug trafficking is the most related to the present study. In particular, Berlusconi et al. (2017), Giommoni et al. (2017), and Aziani et al. (2019) use the UNODC data at the country-pair level to assess how bilateral migrant stock, among other factors, correlates with bilateral drug seizures. They consistently find that migrant stock is positively associated with drug trafficking. However, their analysis has three limitations. First, they do not use exogenous variation in bilateral migrant stock between countries, which may bias their results if unobserved bilateral factors, such as geographic similarity or cultural ties, drive both migration and smuggling. Second, they do not include origin or destination fixed effects, so unobserved country-specific factors may similarly cause omitted variable bias. Third, their analysis is at the country-pair level, and thus even if they had included fixed-effects, unobserved national policies vis-a-vis a partner country may still bias the results.

This paper also relates to the extensive literature on the consequences of globalization. While many studies in economics have estimated positive effects of immigrants on *legal* trade[3], none have done so for *illegal* trade. Separately, there has been substantial interest in the effects of immigration on crime rates. I provide evidence for a new mechanism linking migration and crime, specifically that migrant connections to their home country facilitate smuggling. Most of these studies find that the effect of immigration on crime is generally small but depends on the formal labor market returns for migrants.[4] I find support for such a mechanism by finding that migrant legal status is an important determinant for drug trafficking.

In addition, this paper follows a strand of mostly theoretical papers on the economics of smuggling dating back to Bhagwati and Hansen (1973).[5] More recent empirical work on smuggling has been done by Fisman and Wei (2009) on the smuggling and misinvoicing of cultural goods and Akee et al. (2014) on the determinants of human trafficking. I expand upon this literature by studying the smuggling of illegal drugs, one of the most important and consequential illegally smuggled goods.

This paper proceeds as follows. Section 2 introduces the data, some stylized facts about drug trafficking, and validates the drug seizures data as a proxy for actual drug flows. Section 3 presents my empirical strategy, results, and some interpretation, with Section 4 discussing and assessing the contribution of several potential mechanisms. In Section 5 I microfound

[3]See, for example, Gould (1994), Head and Ries (1998), Rauch and Trindade (2002), Combes et al. (2005), Cohen et al. (2017), and Parsons and Vézina (2018).

[4]See, for example, Spenkuch (2013), Bianchi et al. (2012), Bell et al. (2013), and Miles and Cox (2014).

[5]Other notable entrants in this literature are Grossman and Shapiro (1988) and Thursby et al. (1991).

my estimating equations from standard trade theory. Section 6 concludes.

2 Data

2.1 Drug Trafficking Data Description

Having a credible measure of illegal drug flows is crucial to my analysis. Since direct measurement in an illegal market context is very challenging, I use an indirect measure of trafficking: the amount of drugs seized on a bilateral link, under the assumption that seizures are correlated with actual flows of illicit drugs.[6] This approach is similar to other studies of illicit behavior where direct observation is difficult or impossible. For example, Dell (2015) uses local drug-related violence as a proxy for drug trafficking through a location.[7]

To proxy for drug trafficking flows, I use a novel dataset of individual wholesale-level drug seizures at the bilateral level compiled by the United Nations Office of Drugs and Crime (UNODC). An observation in these data is a single drug seizure event and details the type of drug, the amount seized, the country from which the drugs were trafficked, and, the location of the seizure. By including both the locality of a seizure and its country of departure, I observe a bilateral linkage for each seizure event.

Reporting drug seizures to the UNODC is voluntary, however, which leads to selection in which countries report, how often they report, and what fraction of drug seizures they report to the UNODC. To resolve this problem I focus on Spain, a country that reports a substantial number of drug seizures to the UNODC nearly every year (see Figure 1) and reports higher quality data than other countries.[8]

The data Spain reports to the UNODC comes from the Statistical System of Analysis and Evaluation on Organized Crime and Drugs (SENDA), a centralized repository of information on organized crime and the illegal drug trade. This database is filled out by three national reporting agencies: the National Police, the national anti-smuggling agency (Guardia Civil), and the Customs and Excise Department. These agencies are reporting both seizures enacted by their own personnel as well as those conducted in concert with or exclusively by local law enforcement authorities.

Country of origin for each drug seizure in the dataset is assigned based on subsequent

[6] I discuss measurement error in the context of estimation in Section 3.

[7] Another example is Dube et al. (2016) who uses illegal crop eradication as a proxy for cultivation.

[8] For example, amount variables describing the hiding place of seized drugs, the installation in which they were seized, the mode of transport, and the routing of the drugs, seizures reported by Spain were missing only 20% of values for these irregularly reported variables between 2011 and 2016. Meanwhile, Spain reported the most seizures of any country during this period, nearly 10,000. By contrast, the median number of seizures reported was 18 and the mean fraction of values of the aforementioned variables missing was 33%.

investigation, and captures the most recent foreign country the drugs were in and not the country in which they were produced. For some drug interdictions, assignment of origin country is fairly straightforward. For example, for drugs seized from airline passengers upon arrival at an airport, the origin country is the passenger's departure country. For the case of cargo ship containers, a range of documents are checked, including the bill of lading, the commercial invoice, the certificate of origin, customs clearance forms and the relevant letter of credit. In the case of so-called "narco-boats" that transport hashish resin in the Strait of Gibraltar unless proven otherwise their country of origin is considered to be Morocco. 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 is determined based on information obtained from investigations that have been carried out. If a person is arrested within Spain for drug trafficking but outside an airport or port, the country of origin of the drugs will be determined on the basis of the investigations that are carried out or any subsequent checks that may be made on the statements made voluntarily by the arrested person. [9]

To compute the value of illegal drug seizures, I use illegal drug prices reported by the Centre of Intelligence against Organized Crime at the Spanish Ministry of the Interior.[10]

In Table 1, I show summary statistics of the 9,880 individual drug seizures for Spain for the study period. Three facts emerge: (i) nearly all drugs seized by Spanish authorities are cocaine or heroin, with negligible amounts of amphetamines and heroin; (ii) Africa and South America are the primary origins of these drugs, with North America also making up a non-trivial share; (iii) the distribution of drug seizure amounts is right skewed, with many moderate sized seizures (the median seizure value is $43,796) and a few huge seizures (the mean seizure value is $593,795). In addition, the set of countries from which Spain imports illegal drugs is highly concentrated for heroin, amphetamines, and cannabis, but disbursed for cocaine, as shown in Figure 2. Also, many provinces within Spain receive imports of illicit drugs, as shown in Figure 3.

2.2 Validation Exercise

I now turn to validating that the drug seizures data capture real drug smuggling flows. Given perfect information, I would correlate seizures with actual flows. However, I cannot directly observe real flows, so I turn to an alternative, albeit more indirect, method of validating the

[9]The preceding discussion is based on responses to my own information requests from the Spanish Ministry of the Interior.

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

seizures data. This method estimates the predictiveness of drug seizures for drug availability at the destination level, rather than the bilateral level, since I observe the former but not the latter.

I test how much seizures of drugs coming in from outside a region correspond to the availability of drugs in that region.[11] To build confidence that the seizures data do in fact capture local drug availability, I correlate the amount of drugs seized in a province and originating from a foreign country with survey-based measures of drug availability in the province using the Survey on Alcohol and Drugs in Spain (EDADES).

The EDADES is a nationally representative biennial survey on substance use in Spain of about 25,000 respondents per survey. Respondents are asked such questions as,

- "How easy is it for you to obtain [cannabis/cocaine/heroin] within the next 24 hours?"
- "Thinking about where you live, how important of a problem do you think illegal drugs are?"
- "How often in your neighborhood are there drugged people on the ground?"

I aggregate responses from the 2011, 2013, and 2015 survey rounds up to the province level and correlate these to measures of drug seizures from the UNODC over this period, also aggregated to the province in which the seizure occurred.

It is ambiguous a priori how drug seizures will vary with drug availability in a locale. Seizures may be negatively correlated to local drug availability if seizures serve as an effective deterrent and substantially reduce local drug supply. However, seizures may be factored into drug smugglers' decisions and therefore have no deterrent value, which would result in a positive correlation between seizures and local drug availability. For example, in one study of a massive drug bust in the United States of nearly a third of the methamphetamine precursors in the country, Dobkin and Nicosia (2009) find that drug prices rose in the short run but had returned to the pre-seizure levels within 4 months; purity levels returned to their pre-seizure level within 18 months.

I find that seizures positively correlate with a wide range of measures of local drug availability. In Figure 4 I plot the correlation coefficient between the fraction of respondents stating it was impossible, difficult, relatively easy, or very easy to obtain a particular drug (cannabis, cocaine, or heroin) within 24 hours with the amount of that drug seized in the province per capita between 2011 and 2016. Consistent with seizures corresponding to real flows of illicit drugs, I find that the higher the fraction of respondents declaring it "impossible"

[11] Some drugs are re-exported on to further destinations; as long as some of the inflows into a destination are consumed locally, seizures should positively correlate to local drug availability. In addition, marijuana may be produced locally, but this is estimated to be a tiny portion of the market by Alvarez et al. (2016).

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

In Figure 5 I plot the correlation coefficients of various measures of local drug availability and use to the value of all seizures per capita. The measures of drug availability and use are the fraction of respondents replying (i) "very" to "How important of a problem do you think illegal drugs are?", (ii) "frequently" or "very frequently" to the questions about how often they witness evidence of local drug use or sales in their neighborhood.[12] For each survey question, seizures vary positively with local drug availability.

2.3 Other Data Sources

I also use data from more conventional sources.

To measure migrant stocks and flows, I use the 2001 and 2011 Spanish Census from the National Institute of Statistics via IPUMS (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 nationality countries differs for the two Census waves, I aggregate countries into the smallest consistent units allowable.

In my bilateral specification, I also control for distance in kilometers between the Spanish province and foreign countries taken from Peri and Requena-Silvente (2010).

3 Empirical Analysis

I am interested in the causal effect of migrant networks on drug trafficking. I explore this relationship in two ways. First, I estimate a gravity equation using data at the bilateral level, allowing me to assess the extent to which more migrants from an origin in a destination raises the amount of drugs trafficked on that bilateral link. Second, I estimate a destination-level specification, which is informative about how more migrants in a region overall raises illegal drug imports.

As an example of the gravity relationship which I explore with greater rigor in Section 3.2, I consider the case of Morocco, a major source of both immigrants and cannabis flowing into

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

Spain. Spatially, there is substantial overlap between the migrant network and the location of seizures of cannabis coming from Morocco, as shown in Figure 6. To more formally evaluate the relationship between migrant networks and drug smuggling, I next estimate this relationship at the bilateral and destination levels in the country of Spain.

3.1 Spanish Context

Spain is an important entry point for many drugs sold in Europe; the value of total drug seizures in Spain amounts to nearly 4 percent of the total amount of illegal drugs consumed in Europe.[13]

Spanish drug policy focuses on "harm-reduction". Both personal use of and production for personal use of drugs are permitted but drug dealing or trafficking is punished with severe prison sentences (Kleiman and Hawdon, 2011). In addition, while there is limited domestic production of marijuana, much of it is imported, and all cocaine and heroin are imported since they are produced in a select few countries in the world. In particular, cocaine is produced almost exclusively in Colombia, Bolivia, and Peru, while heroin is primarily produced in Afghanistan.[14]

Finally, as shown in Figure 7, Spain has experienced significant in-migration in the last three decades, with the proportion of migrants in the population rising from 2 percent to over 13 percent between 1991 and 2011.

3.2 Bilateral-level

Econometric Specification

I now turn to estimating the effect of bilateral migrant networks on bilateral drug trafficking. Ideally, I would regress actual illicit drug flows $X_{o,d}$ between origin country o and destination province d on migrant stocks. However, I cannot observe illicit drug flows, thus necessitating a latent variables approach. First, I note that bilateral drug seizures $S_{o,d}$, which I do observe, is equal to the product of enforcement intensity $E_{o,d} \in [0,1]$ (also not observed) and actual drug flows; that is, $S_{o,d} = E_{o,d} X_{o,d}$. Next, taking logs, I note that $\ln X_{o,d} = \ln \frac{S_{o,d}}{E_{o,d}} = \ln S_{o,d} - \ln E_{o,d}$ such that $E_{o,d} \neq 0$. The assumption $E_{o,d} \neq 0$ implies that I assume bilateral pairs with no seizures must also have no illicit drug smuggling.

[13]Using the UNODC data I calculate that Spain seized on average almost 1 billion dollars in illicit drugs between 2011 and 2016; the EMCDDA and Europol (2016) estimate the size of the entire European market to be over $26 billion.

[14]No countries other than Colombia, Bolivia, and Peru are listed in official U.S. estimates of cocaine production. Afghanistan is estimated to produce 80% of world heroin, with Burma, Colombia, Guatemala, Laos, Mexico, and Pakistan making up the balance. See page 23 of U.S. State Department (2019).

I estimate a gravity equation of the form,

$$\begin{aligned} \ln S_{o,d} - \ln E_{o,d} &= \alpha_o + \alpha_d + \beta g\left(M_{o,d}\right) + \delta \ln(Dist_{o,d}) + \tilde{\varepsilon}_{o,d} \\ \ln S_{o,d} &= \alpha_o + \alpha_d + \beta g(M_{o,d}) + \delta \ln(Dist_{o,d}) + \varepsilon_{o,d} \end{aligned} \tag{1}$$

where $g(M_{o,d})$ is some increasing function of the stock of migrants from o living in d, $Dist_{o,d}$ is the distance in km between o and d, α_o and α_d are origin and destination fixed effects, respectively, and $\varepsilon_{o,d} = \tilde{\varepsilon}_{o,d} + \ln E_{o,d}$.

The origin country and destination province fixed effects are key to my identification strategy. The origin fixed effect α_o controls for, among other factors, the economic development, institutions, and crime in the origin country, as well as national-level policies of Spain vis-a-vis origin country o. Similarly, the destination fixed effect α_d similarly controls for factors of province d common across origins, such as the province's police force strength and the economy of d.

I make two adjustments to Equation 1 for the empirical analysis. First, I calculate $g(M_{o,d})$ as the log of 1 plus the migrant stock measured in thousands, as this functional form follows from the specification tests suggested by Burchardi et al. (2019).[15] Moreover, my results are robust to other functional forms as well as non-parametric estimation. Second, I replace the dependent variable $\ln S_{od}$ with $\ln(S_{od} + 1)$ or with a dummy for whether any seizure occurred to avoid dropping bilateral links with no seizures, as these make up more than half my sample.

Table 2 shows the estimated relationship between migrant stock and the likelihood of a seizure occurring on a bilateral link (column 1) and the log of 1 plus the amount of drugs seized on a link (column 2). I find that migrant network size is positively correlated with both the extensive margin and the amount of drugs trafficked.

Instrumental Variable Approach

There may be unobserved factors driving both migration and drug trafficking, such as bilateral enforcement intensity as demonstrated in Equation 1. For example, one province's police force may direct greater scrutiny towards particular nationalities relative to other Spanish provinces, which may reduce immigration and drug smuggling from that origin

[15] See Figure 13, which plots the binscatter between the migrant stock and a dummy for any seizure occurring on a bilateral link. The figure shows a concave relationship between the two, suggesting a log functional form. In addition, similar to Burchardi et al. (2019), I estimate $\mathbf{1}\left[Seizures_{o,d} > 0\right] = \delta + \beta \ln\left(1 + \pi M_{o,d}^{2011}\right) + \varepsilon_{o,d}$ in non-linear least squares and obtain $\hat{\pi} = 0.002$, which suggests measuring migrant stock in thousands.

to the province. To obtain variation in migration exogenous to such concerns, I follow Burchardi et al. (2019) and develop instruments for bilateral migrant stock using a set of leave-out push-pull instruments. These instruments produce exogenous variation in bilateral immigrant inflows. I use two decades of inflows during a period of unprecedented immigration into Spain to predict current bilateral migrant stocks.

The intuition of this instrument works by predicting bilateral migration flows from other bilateral migrant flows. For example, suppose we want to predict the number of Moroccans settling in the province of Granada. The instrument will do so by predicting Moroccans will settle in the province within Spain in which large numbers of migrants from other countries are also settling. Similarly, if many immigrants are settling in a particular province, then an immigrant arriving from a particular origin country will be predicted to settle in that province.

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

$$\tilde{I}^{IV,t}_{o,d} = I^t_o \times \frac{I^t_d}{I^t}, \tag{2}$$

where I^t_o is the number of immigrants from origin o coming to Spain in decade t, I^t_d is the number of immigrants from all origins settling in destination province d in decade t, and I^t is the total number of immigrants arriving in Spain in decade t.[16]

However, if immigrant inflows are correlated between similar origin countries or between similar Spanish provinces, then predicting bilateral flows between o and d using equation 2 would fail the exclusion restriction. For example, if both Moroccan and Algerian immigrants go to the province of Granada due to their similar Mediterranean climates, then Moroccan migration to Granada will be predicted, by Algerian migration so long as Algerian migration to Granada is nontrivial, which are both jointly predicted by a third factor, climate, which may also affect drug trafficking (for example, if calm weather facilitates smuggling by sea). To avoid such endogeneity, I again follow Burchardi et al. (2019) and leave out both the continent of origin country o and the autonomous community (the highest-level administrative unit in Spain) of province d to construct the instrumental variable defined as

$$I^{IV,t}_{o,d} = I^t_{o,-a(d)} \times \frac{I^t_{-c(o),d}}{I^t_{-c(o)}} \tag{3}$$

[16]An inflow is defined as a person interviewed for the 2001 or 2011 Spanish census with a nationality from another country who arrived in the 10 years prior to the survey.

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.

Results

Table 3 shows the estimation results for the instrumented gravity specification. Column 1 shows the first-stage, with both instruments having positive and statistically significant coefficients and the first-stage F-statistic surpassing conventional threshold levels. In column 2 I estimate Equation 1 on the extensive margin of drug trafficking while instrumenting for migrant stock using two decades of exogenous predicted immigrant inflows. The coefficient estimate of the effect of migrant network size on the likelihood of drug trafficking on that bilateral link is 0.105 (SE=0.039), which is statistically significant at the 1% level. This estimate implies that at the mean level of bilateral migrant stock, 933, a 10% increase in bilateral migrant network size raises the likelihood that the link will be used for drug trafficking by 0.5 percentage points.[17] Similarly, in column 3, the coefficient estimate of migrant network size on the log amount of drugs seized is 2.33 (SE=0.56), which implies that a 10% increase in migrant stock relative to the mean raises the amount of drugs trafficked by 12%.[18] This is in line with other estimates in the literature examining the effect of migrant networks on legal trade.[19]

Seizures and Enforcement Intensity

Robustness to Functional Form

In my main specification, equation 1, I measure the endogenous variable of interest, migrant network size, as the log of one plus the number of migrants measured in thousands, $g(M_{o,d}^{2011}) = \ln\left(1 + M_{o,d}^{2011}\right)$ which follows from Burchardi et al. (2019) and the diagnostic test they use to obtain their functional form (i.e. non-linear least squares estimation of $\mathbf{1}\left[Seizures_{o,d} > 0\right] = \delta + \beta \ln\left(1 + \pi M_{o,d}^{2011}\right) + \epsilon_{o,d}$). I perform several robustness checks on my baseline functional form assumption.

First, I estimate my baseline specification across a range of functional forms of migrant network size, with results shown in Tables 10 and 11. In addition, I estimate $g(M_{o,d})$ from

[17]Using $\hat{\beta} = 0.105$ from column 2 in Table 3, we have: $\mathbb{1}\left[S_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 933\right] = 0.105\left(\ln\left(1 + \frac{933\times1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.0049$.

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

[19]See, for example, Parsons and Vézina (2018), who estimate the effect of a 10% increase in migrant stock raises the amount of legal trade by 4.5% to 13.8%.

Equation 1 non-parametrically following Chetverikov and Wilhelm (2017), which I depict in Figure 8, and also find that drug trafficking rises in migrant network size. Finally, I estimate my main effect with Generalized Method of Moments using moment conditions

$$E\left[\begin{pmatrix} I_{o,d}^{IV,1991-2001} \\ I_{o,d}^{IV,2001-2011} \\ \left(I_{o,d}^{IV,1991-2001}\right)^2 \\ \left(I_{o,d}^{IV,2001-2011}\right)^2 \end{pmatrix} \times \left(Y_{o,d} - \alpha_o - \alpha_d - \beta_1 \ln(\pi_1 M_{o,d}^{2011} + 1)\right)\right] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

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

for dependent variable $Y_{o,d} \in \{\ln(S_{o,d}+1), \mathbf{1}[S_{o,d} > 0]\}$ and instrument set $Z_{o,d} = \Big(I_{o,d}^{IV,1991-2001}, I_{o,d}^{IV,2001-2}$ Including a moment for the constant, this yields 163 moments. I cluster standard errors by province.

Table 4 shows the results. My estimates of (π_1, π_2) closely match my baseline functional form assumption of $\pi_1 = \pi_2 = \frac{1}{1000}$. In addition, the estimates of (β_1, β_2) also are statistically indistinguishable from my baseline coefficient estimates. At the point estimates, I find that a 10% increae in bilateral migrant stock relative to the mean raises the probability of a seizure occuring on a bilateral link by 1.1 percentage points and the value of drugs seized by 20 percent.

Robustness to Sample

I also estimate my baseline effects using a variety of samples. Figure 9 shows the distribution of β estimates from equation 1 when I drop one origin country at a time for both dependent variables, $\mathbf{1}[S_{o,d} > 0]$ and $\ln(S_{o,d} + 1)$. The histograms show that I estimate a positive β regardless of which country I drop from the sample, suggesting that no single country drives the results.

I also estimate β separately by type of drug. For cannabis and cocaine, I estimate positive and statistically significant effect sizes. For heroin and amphetamines, the effect is close to zero. However, heroin and amphetamines represent less than 1% of drugs seized by Spain as shown in Table 1 and therefore these estimates are based on very limited data.

Legal Trade

To gauge the magnitude of my effect size relative to the effect of migrant networks on legal trade, I also estimate the relationship between migrant networks and legal trade. I do this via the Generalized Method of Moments with moment

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

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

$Z_{o,d}=\left(I^{IV,1991-2001}_{o,d}, I^{IV,2001-2011}_{o,d}, (I^{IV,1991-2001}_{o,d})^2, (I^{IV,2001-2011}_{o,d})^2, (I^{IV,1991-2001}_{o,d}\times I^{IV,2001-2011}_{o,d})\right)'$.[20]

I estimate that a 10% rise in migrant network size increases legal trade by about 13%, a magnitude comparable to the effect of migrant networks on illegal drug smuggling.[21]

4 Understanding the Effect of Migrant Networks on Trafficking

Migration can facilitate the movement of illegal goods in three main ways: (i) by reducing trade costs, since most illegal drugs are not consumed in the same country in which they are produced, (ii) by expanding the pool of people willing to engage in trafficking, since in many countries migrants face barriers to succeeding in the formal labor market, and (iii) by raising the demand for illegal drugs if migrants' preferences for drugs differ from those of the native-born.

The argument that migrant networks reduce trade costs of illegal goods closely follows that of why migrant networks increase legal trade. Felbermayr et al. (2015) notes that migrant networks can reduce information and search frictions for trade between two locations since trust may be greater within nationality and information travels more smoothly within nationality group. Qualitative studies from the criminology literature provide evidence for this mechanism in the drug trafficking context. For example, in a set of interviews with traffickers jailed the United Kingdom by Matrix Knowledge Group (2007), traffickers stressed the importance of recruiting workers from their social networks[22] (with whom they are likely to share nationality), the importance of greater trust within nationality,[23] and the helpfulness

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

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

[22] "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)

[23] For example, "L-15 [a convicted drug trafficker] was from Ghana. In 2000 he was approached by a Ghanian friend to manage his drug business in the United Kingdom. He was trusted by the dealers he had to manage because they knew his family in Ghana." (Marsh et al., 2012)

of living close to immigrants coming from source countries of illicit drugs in reducing search costs.[24] Additionally, migrant networks raise the cost of opportunistic or cheating behavior by firms within the nationality network, who can be punished for bad behavior by being shunned from business within the network (Rauch and Trindade, 2002).

Migration may also raise illegal drug trafficking if immigrants face barriers to access to legal jobs. In Spain, for example, many immigrants have overstayed their visas to live in the country but have not had their status regularized, thus disqualifying them from legal work opportunities (González-Enríquez, 2009). Such barriers have been found by Freedman et al. (2018) in the United States and by Mastrobuoni and Pinotti (2015) and Pinotti (2017) in Italy to significantly raise the participation of immigrants into criminal activity.

Finally, immigration may raise the demand for illegal drugs if they have stronger preferences for drugs relative to the native-born.

Having documented a quantitatively large causal effect of migrant networks on drug trafficking, I now turn to exploring which mechanisms are driving this effect. The following section presents evidence testing various predictions for these channels.

4.1 Enforcement Intensity

Extensive Margin

I assume that seizures S_{od} are a product of enforcement intensity $E_{od} \in [0, 1]$ and actual illegal drug flows X_{od}.

$$S_{od} = E_{od} X_{od} \tag{4}$$

I observe S_{od} but not E_{od} or X_{od}. However, I make the argument that as seizures change with migrant stock, this is a valid proxy for how actual flows change with migrant stock. Taking the derivative with respect to migrant stock I find

$$\frac{\partial S_{od}}{\partial M_{od}} = E_{od} \frac{\partial X_{od}}{\partial M_{od}} + X_{od} \frac{\partial E_{od}}{\partial M_{od}} \tag{5}$$

While I want to estimate $\frac{\partial X_{od}}{\partial M_{od}}$, I will also pick up changes in bilateral enforcement intensity that result from changes in bilateral migration, $\frac{\partial E_{od}}{\partial M_{od}}$. This may occur if, for example, police target migrant groups for drug trafficking enforcement actions once that group reaches a critical mass.

[24] For example, one convicted trafficker said of importing 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."

In my baseline estimates, I assume $\frac{\partial E_{od}}{\partial M_{od}} = 0$. However, this may be implausible. To gauge the extent to which enforcement intensity variation may affect my results, I estimate

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

for the subset of observations for which I predict that $X_{od} \approx 0$.[25]

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

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

where $\hat{S}_{o,d}$ interacts seizures of drugs originating from o but seized outside the autonomous community of d with the fraction of all drugs from outside o's continent seized in d. Implicit in this formulation is the assumption that (1) on average, other provinces outside d's autonomous community are not discriminating against migrants from o when allocating enforcement resources, and (2) on average, interdiction authorities in d are not discriminating against migrants from outside o's continent.

I show results in table 5 subsetting predicted seizures to below \$1,000. While the point estimate falls between the whole sample and the sample predicted to be on the extensive margin, the two estimates are statistically indistinguishable.

Drug Use

I also estimate the effect of additional immigration to a province on local drug use of the native-born. I do so by replacing the dependent variable in Equation 8 with the fraction of native-born adults who have used drugs, either ever in their life or in the last 12 months:

$$\ln\left(\frac{DrugUsers_d^{Native,2011-2016}}{P_d^{Native,2001}}\right) = \alpha + \beta \ln\left(\frac{M_d^{2011}}{P_d^{2001}}\right) + \epsilon_d \tag{6}$$

where $DrugUsers_d^{Native}$ is some measure of the number of native-born drug users in province d, P_d^{Native} is the native-born population of d, P_d is the population of d, and M_d is the number of migrants living in d. I instrument $\ln\left(\frac{M_d}{P_d}\right)$ using equation 9.

I graphically depict the results in Figure 11. I find that higher proportions of immigrants in a province's population lead to more drug use among the native-born across all drugs except heroin, where the effect is statistically indistinguishable from zero. The effect of a 10

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

percent increase in the proportion of immigrants in a province's population is to raise the prevalence of drug use (across all drugs) by 11 percent.

This is also another check on the validity of the seizures data corresponding to increases in actual availability of drugs at the local level, and not merely variation in enforcement actions.

Quantitative Exercise

Since my main results are an elasticity, I divide equation 5 by $S_{o,d}$ and multiply by $M_{o,d}$ to obtain

$$\epsilon_{S,M} = \epsilon_{X,M} + \epsilon_{E,M} \tag{7}$$

where $\epsilon_{X,Y}$ is the elasticity of X with respect to M.

In my empirical results, I find that a 10% increase in bilateral migration stock raises seizures by 12%, so the left-hand side is 1.2.

Next, I quantitatively consider the effects of a 2 standard deviation increase in the bilateral migrant stock. In particular, I first regress the endogenous variable from my baseline specification, $\ln(\frac{M_{o,d}}{1000} + 1)$, and the instrumental variables on a set of origin and destination fixed effects. I then predict residualized $\ln(\frac{M_{o,d}}{1000} + 1)$ using the IVs. The median of this predicted value is 11 migrants[26] and a 2 standard deviation increase raises this to 332[27]. This represents an increase in migrant stock of 3000%, which would imply a 3600% increase in enforcement intensity if my results were driven entirely by changes in enforcement.

To gauge the size of that increase in enforcement intensity, consider that the EMCDDA[28] estimated the size of the EU market for cocaine and cannabis to be about \$20 billion USD. On average, Spain seized 78% of cannabis and cocaine by value according to the UNODC data. Between 2011 and 2016, on average \$1B was seized of these two drugs in Spain. A lower bound for the fraction of drugs seized in Spain is thus $1/(20 \times 0.78 + 1) \approx 0.06$. Therefore an increase in enforcement intensity of 3600% would raise enforcement intensity to 2.17, which violates the requirement that $E_{o,d} \leq 1$.

4.2 Preferences for Drugs

Atkin (2013) and Bronnenberg et al. (2012) suggest that migrants may share the same tastes for food and other products as consumers in their origin region. To the extent that these

[26] $\approx (exp(0.11) - 1) \times 1000$

[27] Standard deviation is ≈ 0.14.

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

tastes carry over to illicit drugs, more drugs may be trafficked to regions with more migration. To the extent that consumers can differentiate drugs trafficked from different origin countries, more drugs may be trafficked along bilateral links which also experience more migration.

First, I find that migrants consume drugs at a substantially lower rate than native-born Spaniards. Using the EDADES data introduced in Section 2.2 for the years 2005 through 2015 I find that 22% of those born outside of Spain have ever consumed marijuana, cocaine, heroin, or amphetamines compared to nearly 35% of the Spanish-born. This suggests that migrants are not driving increases in the local drug use prevalence.

Second, drugs are unlikely to be differentiable to consumers across trafficking origin. Illegal drugs are generally homogenous goods with little differentiation in the market except by the purity of the drug.

4.3 Trade Diversion

One drawback of the above bilateral-level estimation is that it is not informative about the extent to which the effect of migrant networks on drug trafficking comes from overall increases in drug imports versus trade diversion. For example, trafficking may be higher for bilateral links with more migrants, but drug imports across all origins are not higher when more immigrants move to a province. To estimate the overall impact of migration on drug imports, I estimate a province-level specification.

To do so, I sum the amount of seizures and migrants across origins, normalize by province population, and take logs to obtain

$$\ln\left(\frac{S_d}{P_d}\right) = \alpha + \beta \ln\left(\frac{M_d}{P_d}\right) + \epsilon_d \tag{8}$$

for province population P_d. However, because there might be factors affecting both migration and drug smuggling into a province, I instrument using the previous leave-out push-pull summed across origins and normalized by population

$$I_d^{IV,t} = \sum_o I_{o,-a(d)}^t \times \frac{I_{-c(o),d}^t}{I_{-c(o)}^t} \times \frac{1}{P_d^t} \tag{9}$$

Table 6 shows the results of estimating this province-level specification. In column 1 I show the OLS result, which is that a 10% larger migrant stock in a province raises the amount of drugs seized in that province by over 15%. Column 2 shows the first stage regression, which is strongly positive. Column 3 shows the two-stage least squares, where I find that a 10% increase in migrant stock in a province raises drug smuggling into that province by 14% overall.

4.4 Legal Status of Migrants

Cross-Sectional Evidence

Background. The legal status of migrants may be an important factor shaping the relationship between migrant networks and drug seizures. This may occur for three main reasons. First, legal status provides migrants easier access to the formal labor market, thus reducing the returns to criminal activity relative to the legal labor market. Second, legal status may change the punishment faced by the migrant for a given crime, as deportation or other legal sanctions may result from a crime comitted by an irregular migrant. Finally, legal status may affect the way in which police can investigate crimes, since migrant enclaves with high rates of irregularity may be less likely to report crimes or tip off police to ongoing or future crimes.

In Spain, irregular migrants are defined as those living in the country without a residency permit. Irregular migrants generally enter Spain through legal means (González-Enríquez, 2009). These include migrants who overstay their tourist visas, stay in Spain beyond the terms of their temporary residence permits, and so forth.[29] Moreover, irregular migration is a common phenomenon in Spain among migrants. Surveys of migrants in Spain have found nearly 50% of migrants are irregular (Pajares, 2004; Yruela and Rinken 2005). Díez Nicolás and Ramírez Lafita (2001) found that 83% of immigrants had arrived in Spain without a work permit but nevertheless began to work or look for a job.

Concurrent with high levels of irregularity has been Spain's welcoming attitude to migrants more generally, and irregular migrants specifically. For example, the country regularly provided legal status to hundreds of thousands of irregular migrants in waves of regularizations between 2000 and 2005. In addition, irregular migrants are eligible for access to the country's public healthcare and education systems so long as they register with the local population registry. This creates a strong incentive for irregular migrants to be observed in the official population registry, a fact which I will exploit to measure irregular migration prevalence at the bilateral level.[30]

[29] Irregular migrants who enter Spain via either crossing the Strait of Gibralter by boat or by sneaking into the Spanish North African cities of Ceuta or Mellila are a small fraction of irregular migrants, though they garner a disproportionate share of press coverage (González-Enríquez, 2009).

[30] The population registry is still not a perfect measure for several reasons. First, municipalities differ in their documentation requirements for registration and the degree to which they notify migrants that they must re-register every two years. In addition, according to González-Enríquez (2009), sex workers and migrants from China are less likely to register due to deportation fears. This will impact my estimation strategy only if there is a bilateral-specific measurement error, so origin country-specific migrant behaviors common across all provinces or destination province policies common across all origins will be controlled for by the origin and destination fixed effects.

Measurement. To estimate the prevalence of irregular migrants at the origin country-destination province level, I take the difference between the number of persons appears 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

$$Irregular\ Migrants_{od} = Population\ Registry\ Number_{od} - Residency\ Permits_{od} \quad (10)$$

and then divide by total bilateral migrant stock to obtain the fraction of immigrants in the bilateral migrant network who have irregular status. I do this all 52 provinces in Spain as well as for the 75 origin countries for which I observe bilateral population registry figures and bilateral residency permits in 2011. I estimate that 40% of migrants living in Spain are irregular, a finding consistent with the estimate of González-Enríquez (2009) for 2008.

Estimation. To explore whether irregular migration is an important factor in explaining the connection I find between migration and drug trafficking, modify my baseline specification to include two separate terms for the bilateral migrant stock by regular and irregular status:

$$Y_{o,d} = \alpha_o + \alpha_d + \beta_{irregular} \ln\left(M_{o,d}^{irregular} + 1\right) + \beta_{regular} \ln\left(M_{o,d}^{regular} + 1\right) + \zeta \ln(Dist_{o,d}) + \varepsilon_{o,d} \quad (11)$$

To obtain exogenous variation in irregular and regular bilateral migrant stocks, I also modify the leave-out push-pull instrument predicting immigrant inflows to predict immigrant inflows by legal status. In particular, I interact the leave-out push-pull instrument with the leave-out fraction of migrants with legal status L

$$I_{o,d}^{L,IV,D} = \frac{M_{o,-a(d)}^{L,2003}}{M_{o,-a(d)}^{2011}} \times I_{o,d}^{IV,D}$$

for $L \in \{regular, irregular\}$ and decade D.

Table 7 shows the results for estimating equation 11. I find that a 10% increase in bilateral *regular* migrant stock reduces the likelihood of a drug seizure by 2.5 percentage points and a 10% increase in bilateral *irregular* migration raises the likelihood of a drug seizure by 3 percentage points[31] (column 2) and that a 10% increase in bilateral regular migrant stock reduces the value of drugs seized by 29%, while a 10% rise in the bilateral stock of irregular

[31] Using $\hat{\beta}^{Reg} = -0.535$ from column 2 and mean value of bilateral migrant stock of 933, I find that $\mathbb{1}\left[S_{o,d}^{2011-2016} > 0 | M_{o,d}^{2011} = 933\right] = -0.535\left(\ln\left(1 + \frac{933\times1.1}{1000}\right) - \ln\left(1 + \frac{933}{1000}\right)\right) \approx 0.025$and for $\hat{\beta}^{Irreg} = 0.627$, this is 0.030.

migrants raises the value of drugs seized by 60%[32] (column 4). Taken together, these results suggest migrant legal status is an important determinant of entry into crime. However, my identification strategy cannot separate the two channels of selection (that certain origin-destination pairs tend to select for more irregular migrants) and migration policy (the direct effect of legal status on drug trafficking).

Event Study

In 2005, Spain conducted the largest regularization of irregular migrants in its history, with over half a million migrants obtaining regularization. Any migrant who were registered with their local councils in the population registry as of August 8, 2004, offered a work contract of at least 6 months (3 months if in agriculture) and have no criminal record in their home country or in Spain, with the regularization application generally filled out by the prospective employer. (González-Enríquez, 2009)

I estimate the effect of this extraordinary 2005 regularization at the province-by-year level. I estimate this using the equation

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

when I measure the number of irregular migrants in 2003 as in equation 10. I plot the θ_t coefficients in figure 12, both for $Y_{d,t} = \mathbf{1}\{S_{d,t} > 0\}$ and $Y_{d,t} = \ln(S_{d,t} + 1)$. I find that drug seizures fall following the regularization program, although the effect takes several years to become apparent. This suggests that my cross-sectional result on irregular migrants are driven at least in part by barriers to the formal labor market faced by irregular migrants.

4.5 Drug-Hubness of Origins

I next look at whether drugs being seized are coming from countries which are "hubs" of drug trafficking, that is, they export large amounts of illicit drugs. To do so, I interact my measure of migrant network size with a measure of the extent to which an origin country is a drug hub, defined as either the fraction of total world drug seizures coming from the origin country or the rank order thereof.

Data on world bilateral drug seizures are similarly taken from the UNODC dataset on individual drug seizures that I use for Spain. One drawback of these data for countries other than Spain, however, is that reporting of drug seizures to the UNODC is less frequenty and

[32] Using $\hat{\beta}^{Reg} = -7.364$ from column 4, we have: $\frac{S_{od}^{2011-2016}[M_{o,d}^{2011}=1.1\times 933]}{S_{od}^{2011-2016}[M_{o,d}^{2011}=933]} - 1 = \exp\left(-7.364\left(\ln\left(1+\frac{1.1\times 933}{1000}\right) - \ln\left(1+\frac{933}{1000}\right)\right)\right) - 1 \approx -0.293$. For irregular migration, this is 0.602.

high quality than in Spain. Nevertheless, no alternative data source on country-pair drug trafficking exists so I pursue this analysis using these imperfect data.

In table 8 I show the estimated coefficients. I find that origin country which are significantly involved in drug trafficking, i.e. send substantial amount of illicit drugs to countries other than Spain, are more likely to export drugs to Spain when more migrants from those countries settle in Spain.

4.6 Native Response

Do the native-born enter the drug trafficking market when there are fewer migrants? To answer this question, I estimate

$$\frac{Drug\ \ Arrests_d^{Spanish\ \ Nationality}}{Population_d^{Spanish\ \ Nationality}} = \alpha + \beta \ln\left(\frac{Migrants_d}{Population_d}\right) + \epsilon_d$$

and instrument using the leave-out push-pull summed across origins and normalized by population

$$I_d^{IV,t} = \sum_o I_{o,-a(d)}^t \times \frac{I_{-c(o),d}^t}{I_{-c(o)}^t} \times \frac{1}{P_d^t}$$

As shown below in Table 9, I find that larger migrant shares does not lead to differences in drug trafficking arrest rates of the native-born.

5 Theory

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

In particular, consider the basic setup of Eaton and Kortum (2002).

Gravity. Denote by X_{od} the flow of illegal drugs from origin country o to destination d and by $\tau_{od} \geq 1$ the bilateral trade costs (with $\tau_{dd} = 1$ for all d). Then I have the gravity equation

$$\ln X_{od} = \delta_o + \delta_d + \theta \ln \tau_{od}$$

where for bilateral migrant stock M_{od},

$$\ln \tau_{od} = \gamma_0 \ln t_{od} - \gamma_1 \ln M_{od}$$

where t_{od} are bilateral trade costs when migrant stock is zero. Hence, we have

$$\ln X_{od} = \delta_o + \delta_d + \theta\gamma_0 \ln t_{od} - \theta\gamma_1 \ln M_{od}$$

In practice, bilateral trade costs (when migrant stock is zero) can be expressed as

$$\ln t_{od} = \tilde{f}(gravity_{od}) + \tilde{\varepsilon}_{od}$$

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

$$\ln X_{od} = \delta_o + \delta_d + f(gravity_{od}) + \beta_2 \ln M_{od} + \varepsilon_{od} \tag{12}$$

where $\varepsilon_{od} \equiv \theta\gamma_0\tilde{\varepsilon}_{od}$ and the same applies for $f(\cdot)$ and where $\beta_2 \equiv -\theta\gamma_1$. The unobservable bilateral links that shape trade flows, captured by ε_{od}, also shape billateral migration. Hence, estimating (12) using OLS will yield a biased estimate of β_2 (the combination of the trade elasticity and the impact of migration on trade costs). However, with a valid instrument, we can estimate this combination.

Consumption. Denote by C_d total consumption of illegal drugs in destination d. I have

$$C_d = \frac{1}{\xi}\left(\frac{T_d}{\pi_{dd}}\right)^{\frac{1}{\theta}} \tag{13}$$

where the share of imports to d coming from o is

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

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

$$\pi_{dd} = \frac{T_d(w_d)^{-\theta}}{\sum_o T_o(w_o\tau_{od})^{-\theta}} \tag{14}$$

Combining the equations 13 and 14,

$$C_d = \frac{1}{\xi} w_d \left(\sum_o T_o(w_o\tau_{od})^{-\theta}\right)^{\frac{1}{\theta}}$$

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

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

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

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

Starting from the previous expression, let's substitute in for $d \ln \tau_{od}$ to obtain

$$d \ln C_d = (1 - \pi_{dd}) d \ln w_d + \frac{\pi_{dd}}{\theta} d \ln T_d - \sum_{o \neq d} \pi_{od} \left(\gamma_0 d \ln t_{od} - \gamma_1 d \ln M_{od} \right)$$

and substituting out for $d \ln t_{od}$ (assuming no change in the impact of time-invariant gravity variables) yields

$$d \ln C_d = (1 - \pi_{dd}) d \ln w_d + \frac{\pi_{dd}}{\theta} d \ln T_d + \gamma_1 \sum_{o \neq d} \pi_{od} d \ln M_{od} + \varepsilon_d$$

where $\varepsilon_d \equiv -\gamma_0 \sum_{o \neq d} \pi_{od} d \ln \tilde{\varepsilon}_{od}$. Integrating up to levels and I obtain a province-level specification comparable to 8.

6 Conclusion

The effect of immigration on crime has long been a controversial political issue. In this paper, I contribute to this debate by estimating that migrant networks are an important determinant of international drug trafficking, on par with the effect of migrant networks on legal trade found in other studies. In addition, I find that this effect is driven by supply-side rather than demand-side forces, where immigrants reduce transaction costs across space but do not carry with them higher demand for drugs relative to the native-born.

An important caveat is that immigrants generate a range of effects on their host countries, from wages of the native-born to innovation to consumer choices and so on. Hence, generalizing welfare effects of immigration from just one outcome, as is the subject of the present study, is not warranted. Instead, future research should carefully weigh each effect of immigrants in a comprehensive framework.

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Table 1: Summary Statistics of Drug Seizures in Spain

Percent of value seized:	
Drug type:	
Amphetamines	0.2
Cannabis	44
Cocaine	56
Heroin	0.4
Origin Continent:	
Africa	43
Asia	0.7
Europe	0.4
North America	11
Oceania	0.0
South America	44
Percent of countries with >0 seizures	40
Value of amount seized ($):	
Mean	593,795
Median	43,796
Maximum	192,700,768
Num. of seizures	9,880

Notes: This table presents summary statistics for the United Nations Office of Drugs and Crime Individual Drug Seizures dataset for Spain between 2011 and 2016.

Table 2: Relationship between Migrant Network Size and Drug Seizures

	(1)	(2)
	$\mathbb{1}\{S_{od}^{2011-2016} > 0\}$	$\ln\left(S_{od}^{2011-2016}\right)$
$\ln\left(M_{od}^{2011}\right)$	0.138***	1.946***
	(0.0128)	(0.246)
Ln distance	0.00505	0.0690
	(0.0276)	(0.514)
Observations	5564	5564
R^2	0.417	0.461
Dep. var. mean	0.084	1.036
Origin FE	Y	Y
Dest. FE	Y	Y
Ln dist.	Y	Y

$S_{od}^{2011-2016}$ measured as dollars of drugs seized.
Standard errors clustered by 52 provinces in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of Migrant Network Size on Drug Seizures: Bilateral-Level

	(1) First-stage: $\ln\left(\frac{1+M_{o,d}^{2011}}{1000}\right)$	(2) 2SLS: $\mathbb{1}\{S_{o,d}^{2011-2016} > 0\}$	(3) 2SLS: $\ln\left(S_{o,d}^{2011-2016}\right)$
$IV_{o,d}^{2001-2011}$	0.0000370**		
	(0.0000140)		
$IV_{o,d}^{1991-2001}$	0.000154***		
	(0.0000258)		
$\ln\left(1+M_{o,d}^{2011}\right)$		0.106***	2.343***
		(0.0386)	(0.557)
Observations	5564	5564	5564
R^2	0.698	0.046	0.060
Origin FE	Y	Y	Y
Dest. FE	Y	Y	Y
Ln dist.	Y	Y	Y
1st-stg F-stat.	24.0	24.0	24.0

Standard errors clustered by 52 provinces in parentheses

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

Table 4: Effect of Migrant Network Size on Drug Seizures: Bilateral-Level, GMM

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

Standard errors clustered by 52 provinces in parentheses

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

Table 5: Effect of Migration on Drug Seizures: Extensive Margin

	(1) Any Seizures 2011-2016$_{o,d}$	(2) Any Seizures 2011-2016$_{o,d}$
$\ln\left(1 + M_{o,d}^{2011}\right)$	0.106***	0.0541**
	(0.0386)	(0.0255)
Observations	5564	4015
R^2	0.046	0.017
Origin FE	Y	Y
Dest. FE	Y	Y
Ln dist	Y	Y
1st-stg F-stat.	24.0	20.0
Sample	All	< 1000 USD seized

Standard errors clustered by 52 provinces in parentheses

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

Table 6: Effect of Migration on Drug Seizures: Destination-Level

	(1) OLS: Ln amt seized ($) per capita	(2) First-Stage: Ln migr. pop share	(3) 2SLS: Ln amt seized ($) per capita
Ln migr. pop share	1.577***		1.449**
	(0.578)		(0.563)
Predicted migr inflows, 2001-2011		14.22***	
		(1.200)	
Predicted migr inflows, 1991-2001		40.54***	
		(2.492)	
Observations	52	52	52
R^2	0.135	0.933	0.134
1st-stg. F-stat		230.1	230.1

Heteroskedasticity robust standard errors in parentheses

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

Table 7: Effect of Migrant Stock & Irregular Migration on Drug Seizures

	(1) Any Seizures 2011-2016$_{o,d}$	(2) Any Seizures 2011-2016$_{o,d}$	(3) Ln amt seized ($) 2011-2016$_{o,d}$	(4) Ln amt seized ($) 2011-2016$_{o,d}$
$\ln\left(1+M_{o,d}^{2011}\right)$	0.143***		3.362***	
	(0.0374)		(0.487)	
$\ln\left(1+M_{o,d}^{2011,reg}\right)$		-0.122		-0.0625
		(0.0858)		(1.264)
$\ln\left(1+M_{o,d}^{2011,irreg}\right)$		0.403***		5.481***
		(0.0830)		(1.135)
Observations	2771	2771	2771	2771
R^2	0.051	0.038	0.084	0.107
Origin FE	Y	Y	Y	Y
Dest. FE	Y	Y	Y	Y
Ln dist	Y	Y	Y	Y
Kleibergen-Paap F-stat.	58.8	8.4	58.8	8.4

Standard errors clustered by 52 provinces in parentheses.

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

Table 8: Effect of Migrant Network Size by Origin Drug-Hubness

	(1) Any Seizures 2011-2016$_{o,d}$	(2) Ln amt seized (\$) 2011-2016$_{o,d}$	(3) Any Seizures 2011-2016$_{o,d}$	(4) Ln amt seized (\$) 2011-2016$_{o,d}$
$\ln\left(1+\frac{M_{od}^{2011}}{1000}\right)$	0.113***	2.242***	0.146***	3.313***
	(0.0376)	(0.538)	(0.0434)	(0.628)
$\ln\left(1+\frac{M_{od}^{2011}}{1000}\right)$ $\times$ % of seized drugs from o	0.0222	3.182		
	(0.237)	(3.643)		
$\ln\left(1+\frac{M_{od}^{2011}}{1000}\right)$ $\times$ Drug hubness rank			-0.00140**	-0.0499***
			(0.000670)	(0.00999)
Observations	5564	5564	5564	5564
R^2	0.048	0.064	0.060	0.111
Origin FE	Y	Y	Y	Y
Dest. FE	Y	Y	Y	Y
Ln dist	Y	Y	Y	Y
1st-stg F-stat.	24.045	24.045	12.834	12.834

Standard errors clustered by 52 provinces in parentheses.

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

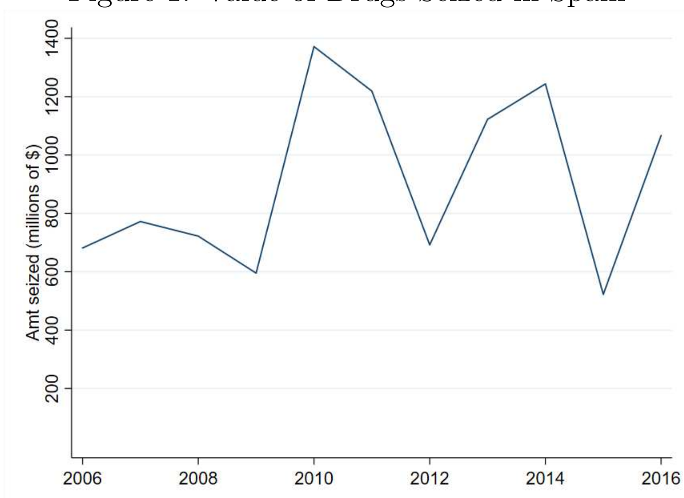
Table 9: Effect of Migrant Share on Rate of Drug Trafficking Arrests of Native-Born

	(1) OLS: Rate of drug trafficking arrests of native-born	(2) First-Stage: Ln migr. pop share	(3) 2SLS: Rate of drug trafficking arrests of native-born
Ln migr. pop share	-0.00000350		-0.0000109
	(0.0000168)		(0.0000237)
Predicted migr inflows, 2001-2011		14.22***	
		(1.200)	
Predicted migr inflows, 1991-2001		40.54***	
		(2.492)	
Observations	52	52	52
R^2	0.000	0.933	.
1st-stg. F-stat		230.1	230.1

Heteroskedasticity robust standard errors in parentheses

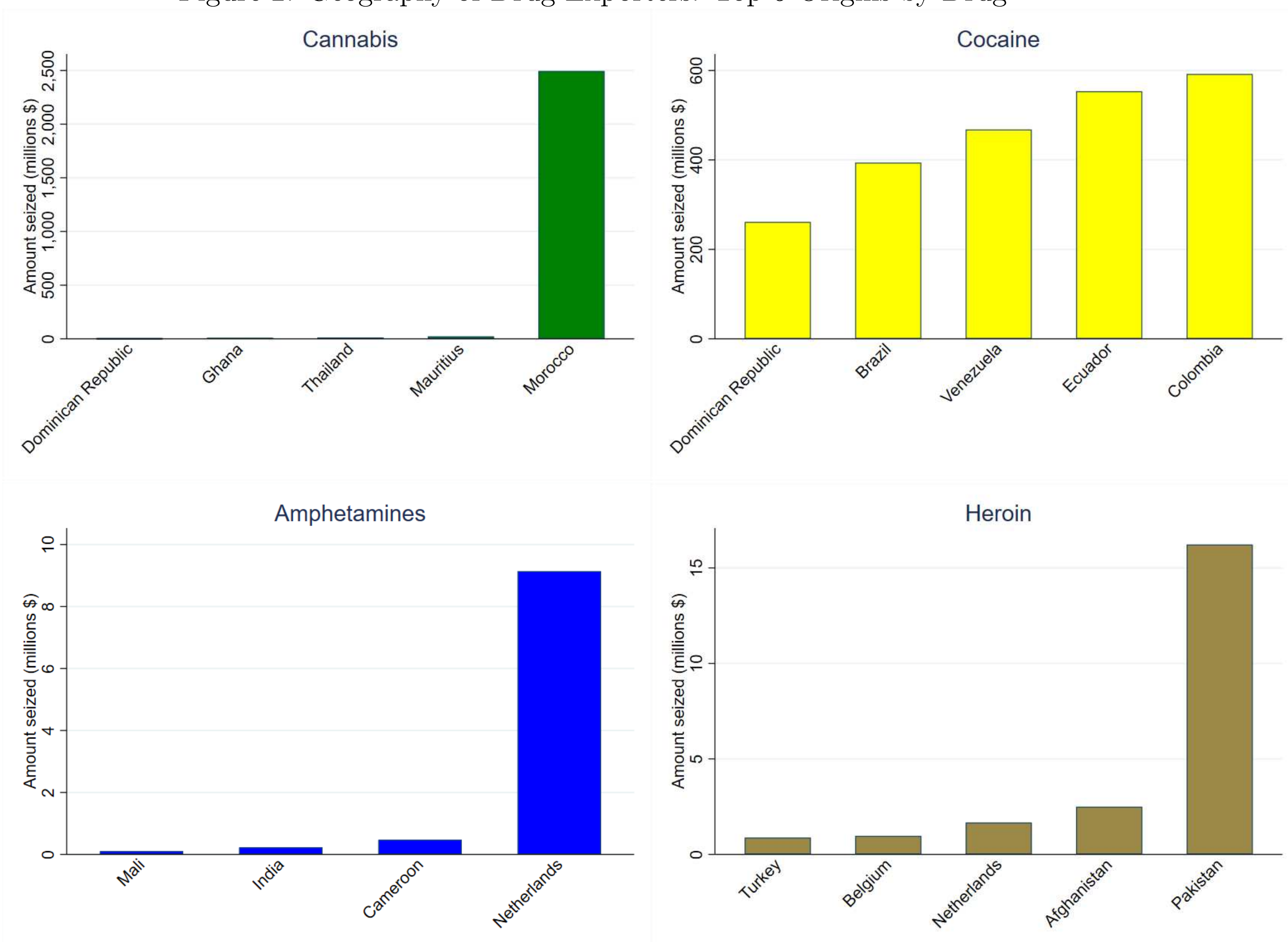
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Value of Drugs Seized in Spain



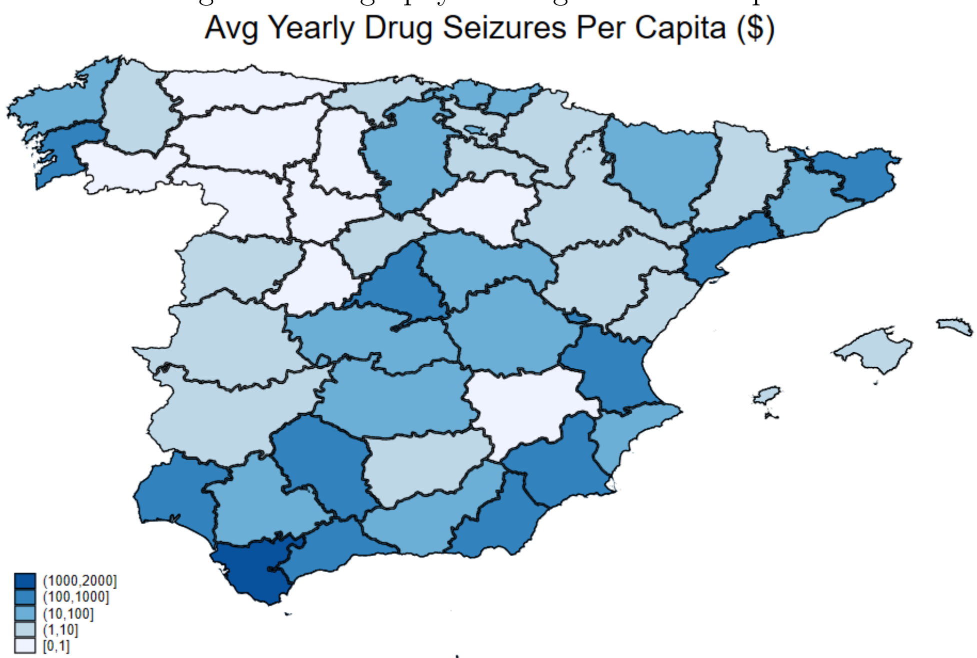
Notes: This figure shows the value of drugs trafficked from foreign countries seized over time by Spanish authorities as reported to the UNODC. Drug prices used are 2012 wholesale prices taken from a survey of Spanish drug prices reported to the UNODC.

Figure 2: Geography of Drug Exporters: Top 5 Origins by Drug



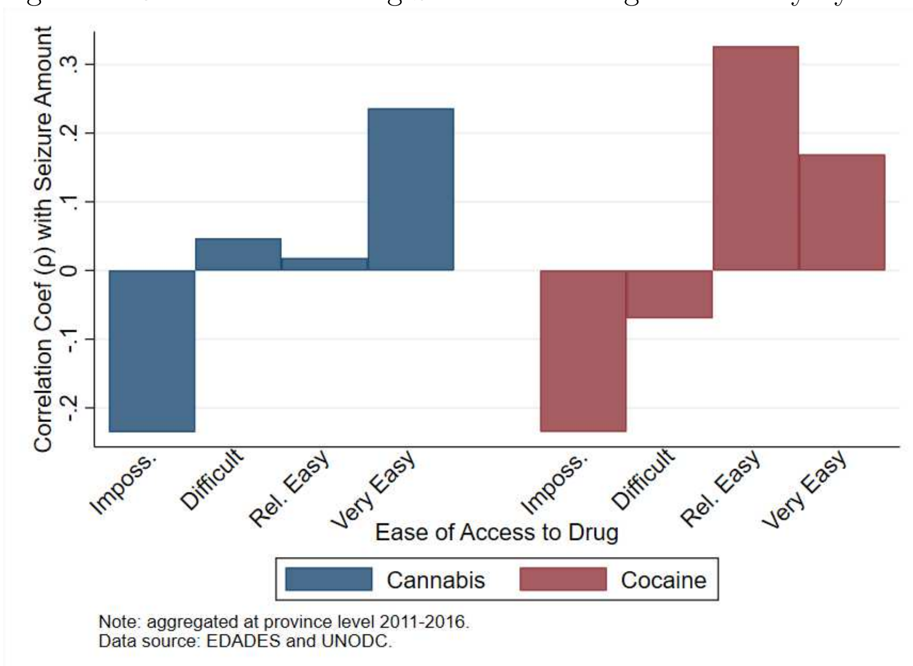
Notes: This figures shows the top 5 exporters of illegal drugs to Spain during 2011 through 2016 by drug as reported by Spain to the UNODC.

Figure 3: Geography of Drug Seizures in Spain



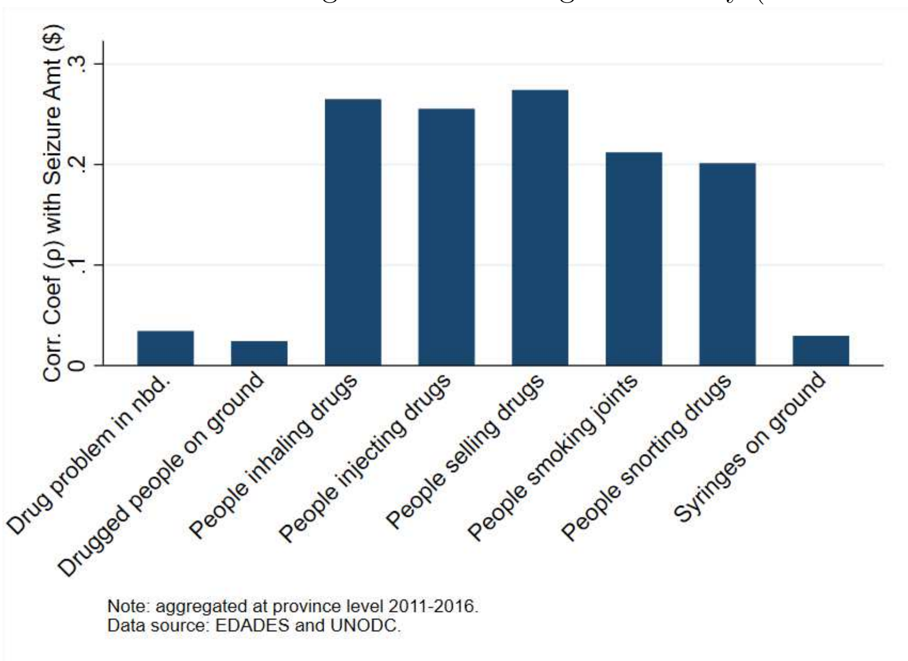
Notes: This figure shows the distribution of drug seizures (measured in dollars by the estimated wholesale value of seized drugs) per capita across Spanish provinces for seizures occurring between 2011 and 2016 as reported by Spain to the UNODC.

Figure 4: Correlation of Drug Seizures to Drug Availability by Drug



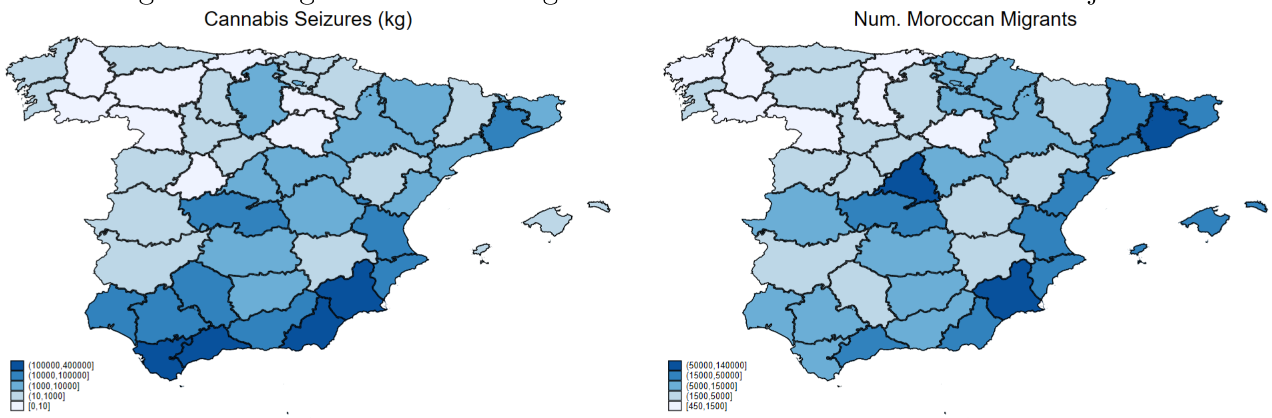
Notes: This figure shows the correlation coefficient between seizures per capita of a particular drug with the fraction of respondents in a province who report finding it impossible/difficult/relatively easy/very easy to obtain that drug within 24 hours averaged over the 2011, 2013, and 2015 waves of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

Figure 5: Correlation of Drug Seizures to Drug Availability (across all drugs)



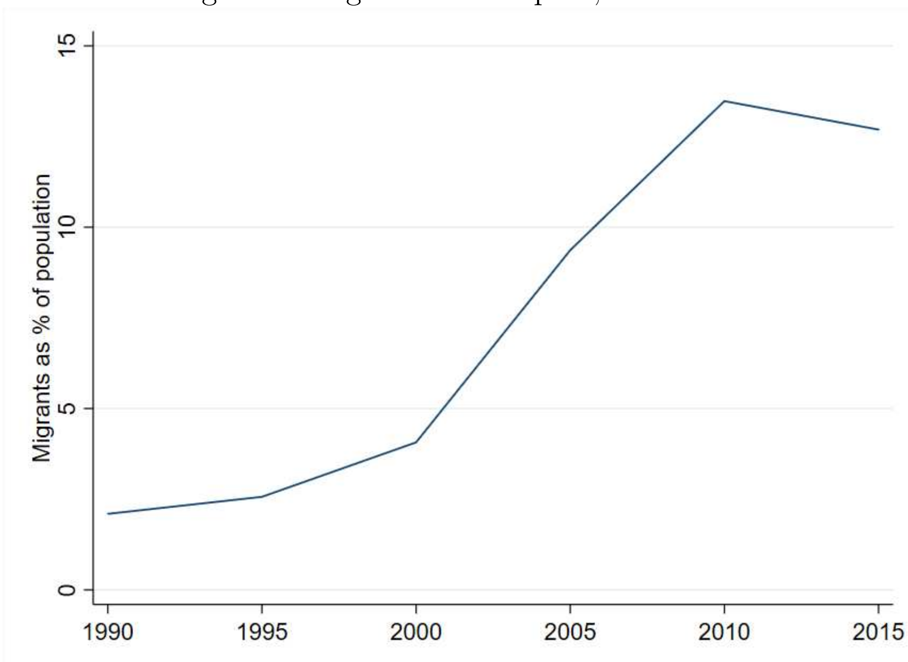
Notes: This figure plots the correlation coefficient between seizures (in dollars) per capita of all drugs (as appropriate) with the fraction of respondents in the province who reported observing the listed drug-related behaviors either "frequently" or "very frequently" or, for the first bar, "very". The behaviors listed are, from left to right: (i) "Thinking about where you live, how important of a problem do you think illegal drugs are?", (ii) "How often in your neighborhood are there drugged people on the ground?", (iii) "How often in your neighborhood are there people inhaling drugs in paper/aluminum?", (iv) "How often in your neighborhood are there people injecting drugs?", (v) "How often in your neighborhood are there people selling drugs?", (vi) "How often in your neighborhood are there people smoking joints?", (vii) "How often in your neighborhood are there people snorting drugs by nose?", (viii) "How often in your neighborhood are there syringes lying on the ground?". As appropriate, I drop marijuana from the drug seizures variable in the correlation, specifically for the questions on people snorting or injecting drugs or syringes being on the ground.

Figure 6: Drug Seizures and Migration: The Case of Morocco and Marijuana



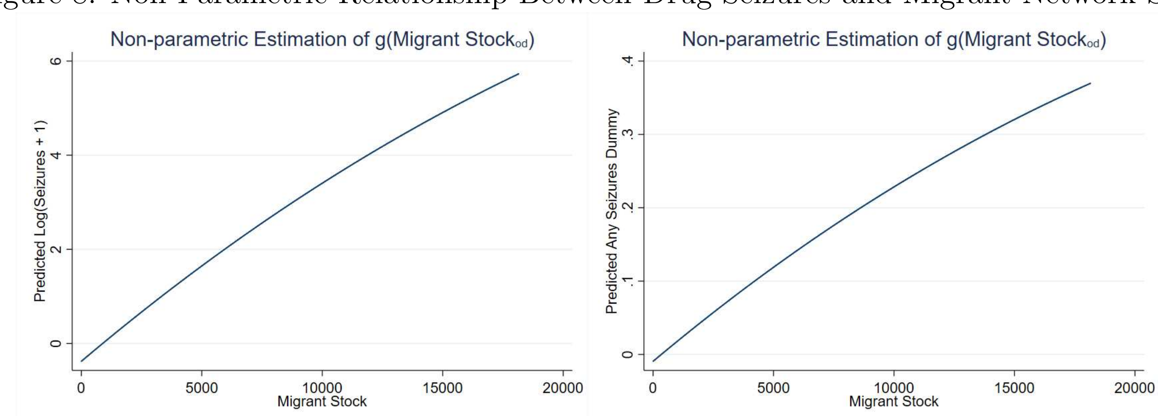
Notes: The figure on the left shows the distribution across Spanish provinces of seizures of marijuana between 2011 and 2016 originating from Morocco; the figure on the right shows the distribution across Spanish provinces of the number of individuals with Moroccan nationality in 2011.

Figure 7: Migration into 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 come from the United Nations Population Division.

Figure 8: Non-Parametric Relationship Between Drug Seizures and Migrant Network Size



Notes: This figure shows the values of $\log(S_{od} + 1)$ (on the left), with S_{od} equal to the value of drugs seized in province d originating from country o, or $\mathbf{1}\{S_{od} > 0\}$ predicted from the non-parametrically estimated function $g(M_{od})$ from Equation 1 on the right. To estimate $g(\cdot)$, I used the Stata program `npiv` developed by Chetverikov et al. (2018).

Figure 9: Effect of Migrant Networks on Drug Trafficking: Dropping Origin Countries

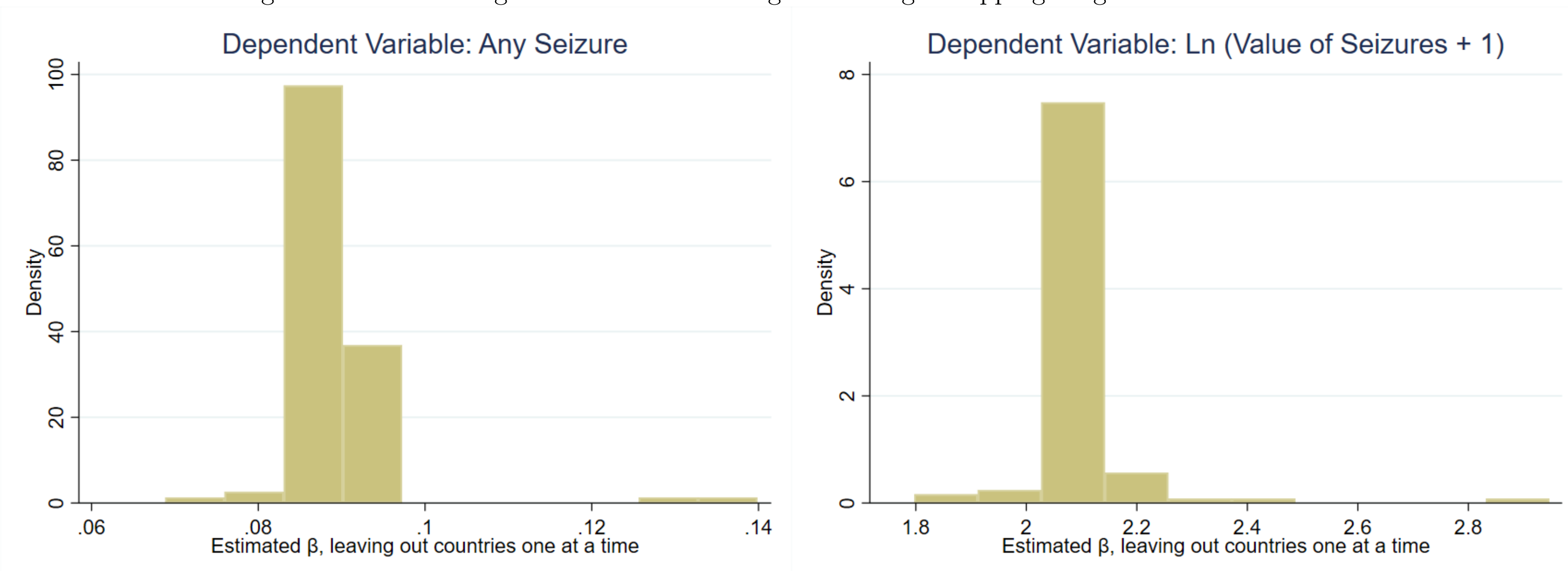


Figure 10: Effect of Migrant Networks on Drug Trafficking: By Drug

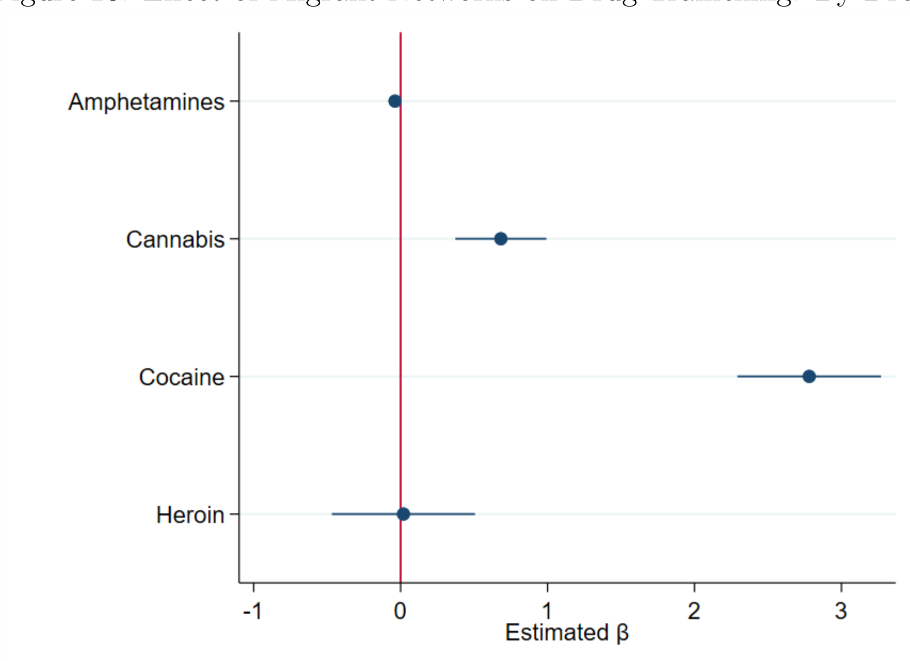
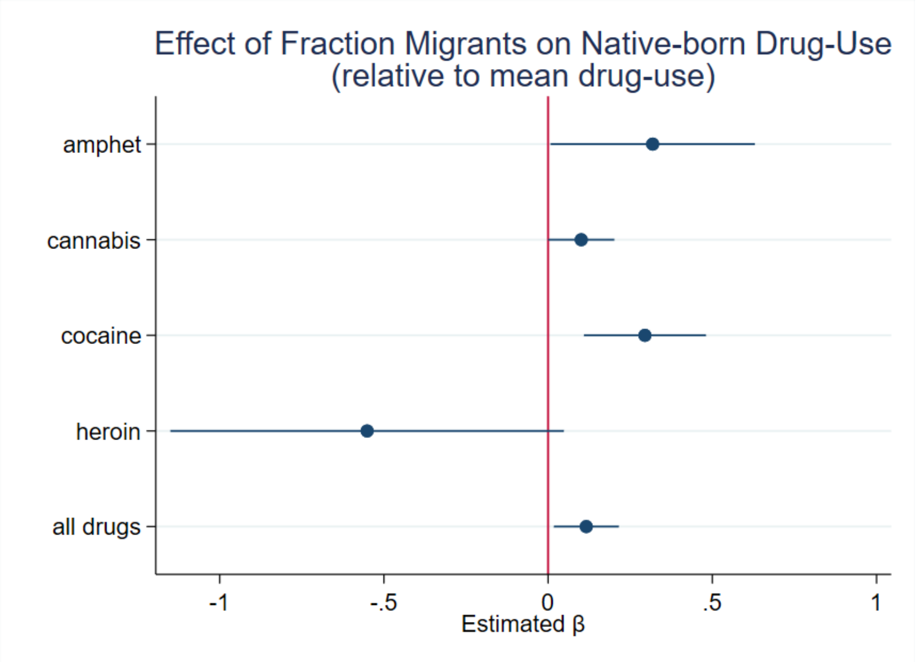
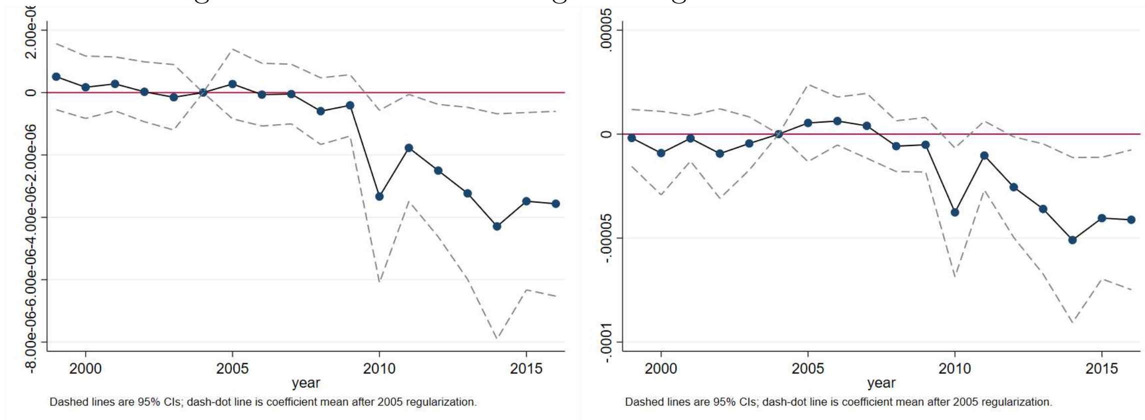


Figure 11: Effect of Immigration on Native Drug Use



Notes: This figure plots the coefficient estimates of β from Equation 6 for each drug (the top four estimates: amphetamines, cannabis, cocaine, and heroin) and for any drug (the last estimate). The effect sizes are normalized by the national average drug use prevalence for each drug type.

Figure 12: Effect of 2005 Migrant Regularization on Seizures



Appendix

Table 10: Robustness to Different Functional Forms, Any Seizure

	(1) Any Seizures 2011-2016$_{o,d}$	(2) Any Seizures 2011-2016$_{o,d}$	(3) Any Seizures 2011-2016$_{o,d}$
$M_{o,d}^{2011}$	0.00000436*		
	(0.00000253)		
$\ln\left(\frac{M_{o,d}^{2011}}{1000}\right)$ (-1 for ∞)		0.0891***	
		(0.0253)	
$\left(M_{o,d}^{2011}\right)^{1/3}$			0.0142**
			(0.00598)
Observations	5564	5564	5564
R^2	0.011	-0.206	0.029
Origin FE	Y	Y	Y
Dest. FE	Y	Y	Y
Ln dist	Y	Y	Y
1st-stg F-stat.	283.263	7.382	51.901

Standard errors clustered by 52 provinces in parentheses

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

Table 11: Robustness to Different Functional Forms, Ln Amount of Seizure

	(1) Ln amt seized (\$) 2011-2016$_{o,d}$	(2) Ln amt seized (\$) 2011-2016$_{o,d}$	(3) Ln amt seized (\$) 2011-2016$_{o,d}$
$M_{o,d}^{2011}$	0.0000985**		
	(0.0000426)		
$\ln\left(\frac{M_{o,d}^{2011}}{1000}\right)$ (-1 for ∞)		1.971***	
		(0.354)	
$\left(M_{o,d}^{2011}\right)^{1/3}$			0.314***
			(0.0914)
Observations	5564	5564	5564
R^2	0.020	-0.842	0.016
Origin FE	Y	Y	Y
Dest. FE	Y	Y	Y
Ln dist	Y	Y	Y
1st-stg F-stat.	283.263	7.382	51.901

Standard errors clustered by 52 provinces in parentheses

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

Figure 13: Binscatter, Any Seizures on Migrant Stock