THE PROMISE OF CROP SUBSTITUTION PROGRAMS: MAKE AVOCADOS, NOT DRUGS

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Abstract

Crop substitution programs have begun to attract the attention of policymakers eager to stem the production of illegal drugs while supporting the poor rural farmers who cultivate such products. However, drug policy researchers argue that such programs are unlikely to succeed due to "balloon effects", the general equilibrium effects of a reduction in supply increasing production elsewhere. I study the context of Mexico, where the production of illegal drugs is roughly estimated to employ up to 450,000 people. I undertake a large remote sensing effort to detect opium poppy in major production zones, and coupled with panel data on the production of other agricultural crops, I estimate elasticities of substitution between illicit and licit crops. I then develop a model to understand what level of subsidies would be necessary to give rise to a substantial reduction of illegal drug production, as well as compare the welfare impacts of a price susbidy program to the effects of eradication campaigns.

Keywords: Crop substitution programs, two stage constant elasticity of transformation functions, general-equilbrium policy analysis
JEL Classification: F14, O13, O19

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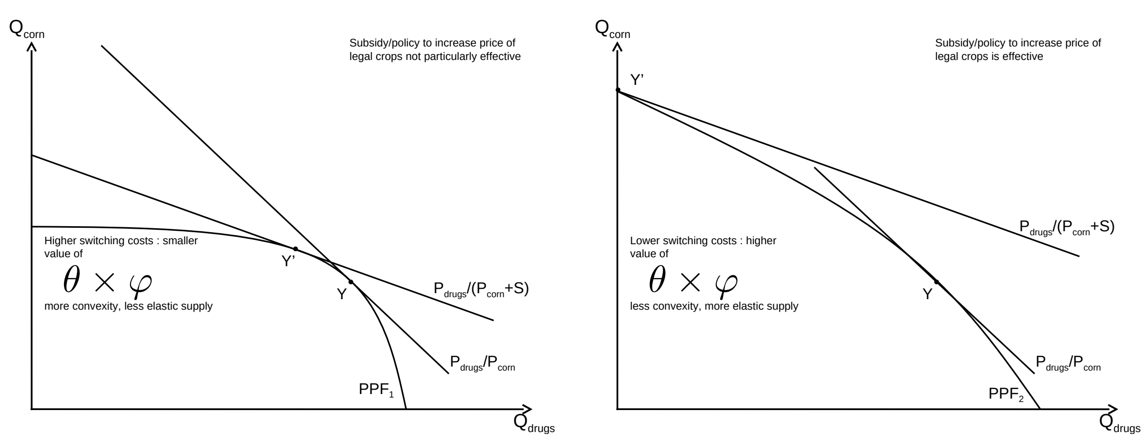
1 Introduction

Regions involved in the production and shipment of illicit drug crops often exhibit high levels of violence, weak or corrupt institutions, elevated risks of extortion of firms, and poor development. Illegal drug production is prominent in many developing countries, with Afghanistan, Colombia, Mexico, Peru, Morocco, Myanmar, Laos accounting for the largest drug producers (UNODC, 2015). Although some of the consequences of criminal organizations involved in the drug trade (often referred to in the literature as drug trafficking organizations, or DTOs) are well documented (particularly that of their violence), less of a focus has been made on the local farmers who often supply crops used to produce illegal drugs to such criminal organizations. For farmers living in rural areas with poor rule of law, high trade costs, inadequate access to working captial, and weak institutions, the cultivation of illegal drugs presents a risky, yet lucrative production activity. This leaves policymakers aiming to stem the production of illegal drugs within their borders with a conundrum: how to stop the flow of drugs (and accompanying violence), while attempting to support the communities in which drug production plays a vital economic role.

A standard approach available to policymakers to mitigate drug production would be a price subsidy enacted on the price of legal crops grown in drug producing regions. However, standard economic theory suggests that the efficacy of a price subsidy will be governed by the substitutability between illegal and legal crops. In a standard production possibilities frontier (PPF), the curvature of the PPF (as measured by the elasticity of transformation) is the primary force which affects the effectiveness of a subsidy program. This is depicted in Figure 1: as the curvature of the PPF increases, the same price subsidy will be more effective at shifting production away from drugs (from point Y to Y'), all else equal.

Figure 1: Elasticity of transformation $\theta \times \varphi$ and subsidy effectiveness



(a) Low elasticity of transformation (b) High elasticity of transformation

This elasticity of transformation may arise from several factors. To conceptualize this, consider the elasticity of transformation to be a product of two parts: $\theta \times \varphi$. θ can be considered to include factors that involve the inherent costs of switching crops, such as the difficulty of obtaining seeds for new crop varieties, the difficulty of learning by doing in agriculture, and other factors that the agricultural economics literature have identified. φ includes factors specific to the cultivation of illegal vs. legal crops: such the stability of state institutions, the ability for farmers to access credit differentially from banks or DTOs, or the likelihood of seizures by the state. Any potential analysis of the effectiveness of subsidies, will therefore need to measure these factors and the impact they play on the degree of substitution between licit and illicit crop production accurately.

Another concern that may limit the effectiveness of crop substitution programs may be the concerns that such programs will lead to spillover effects. In particular, drug policy researchers argue that although subsidies may be effective at reducing drug production in targeted areas, they will yield "balloon effects", where untargeted areas will choose to increase their supply and cancel out any possible reductions in supply coming from targeted areas. These balloon effects will work through the following general equilibrium channel: if areas targeted by the subsidy cause a decrease in the overall supply of illicit drugs, the equilibrium price of those drugs will increase, inducing other (non-targeted) areas to supply more of such products. These effects are likely to be large considering the low elasticities of demand for drugs (Becker et al., 2006)[1]. Therefore, it is worth asking: even if such programs do not reduce drug supply in aggregate, are these policies welfare improving vis-à-vis heavy handed eradication programs?

In this paper, I study the context of Mexico, where illegal drug production, particularly that of opium poppy and marijuana, is significant. Official statistics documenting the size and importance of drug production to Mexico's economy are understandably missing, but rough estimates have suggested that the illicit drug sector in Mexico employs approximately 450,000 people and earns 25 billion in annual profits (Morris, 2012). The DEA Domestic Monitoring Program has documented that in recent years, rural farmers in Mexico have supplied almost 91 percent of heroin found in the United States (of National Drug Control Policy, 2019). Recently, Mexican politicians have expressed interest in developing crop substitution programs, including former heads of military, state governors, and current Mexican President Andrés Manuel López Obrador. However, in Mexico, the success of potential programs remains unclear as there have never been formal attempts at crop substitution.

To make progress in evaluating the potential effects of crop substitution programs, I precede in several steps. I begin by reviewing the history of recent crop substitution programs and of the related economic literature. Then, I discuss the sources of data available to answer this question.

[1] A meta-review finds even more narrowly defined categories of illicit drugs (such as marijuana, heroin, etc.) have very low elasticities of demand, implying very low elasticities of substitution across the more prominent varieties of illicit drugs.

To make progress on studying the scale and extent of illicit drug production in Mexico, particularly that of opium poppy, I develop an algorithm to detect opium poppy using satellite imagery at large scale (in progress). To better understand the economic forces underpinning crop production and substitution, I next develop a theoretical model of licit and illicit crop production and trade that can generate general equilbrium effects of reduced supply caused by a subsidy program. Using the intuition from this theoretical model and the data, I quantify two measures of crop substitution: the degree of substitution within varieties of legal and illegal crops, and the degree of substitution across legal and illegal crops. With these two estimates in hand, I simulate the the effects of a price subsidy on production of licit and illicit crops through the lens of my theoretical model. The last section concludes.

2 Crop substitution programs

In the last decades, national governments, particularly those in Latin America such as Colombia, Mexico, and Peru, have begun to consider alternative programs designed to curb the production of illegal drug crops. The interest in non-militarized responses to prevent drug production such as crop substitution programs has grown as policymakers have become more cogent of the harms of eradication efforts.

While interest has shifted to crop substitution programs, to date the vast majority of government response has been heavy-handed eradication efforts, often times directly or indirectly funded by the United States. In many cases, crop eradication has employed the usage of chemicals sprayed from airplanes or helicopters, some of which (such as glyphosate) are known to be carcinogenic. Other common methods of crop eradication have been seizures carried out using slash and burn techniques. These military interventions are often protested by rural farmers as a loss of a large portion of their income, even nonwithstanding the threat of violence.

The largest example to date of a crop substitution program is from Colombia. The Comprehensive National Program for the Substitution of Crops for Illicit Use (or PNIS, by its acronym in Spanish) was signed in 2016 as part of a peace agreement between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC, in Spanish). Despite payments not beginning until 2016, just the announcement of the program in 2014 was shown to increase drug production in ineligible areas compared to areas eligible for such transfers (Mejía et al., 2019). Additionally, other research has shown that the net effect of anticipation of receiving the payment outstripped the post-treatment reduction in illegal crop growth (Ladino et al., 2019). According to the PNIS text, the law offered the following benefits to each farmer complying with the law: 6 transfers of two million colombian pesos (around 2.5 times the minimun monthly wage), in-kind transfers of 20.8 million COP, and technical assistance for other crops (3.2 million COP). While the results of the policy are yet to be seen, the program has recently gotten off to a rocky start with delayed or outright missing payments promised by the program.

In other settings, the United States has experimented with crop subtitution programs as a method to stem the production of opium in Afghanistan. Initial efforts from 2005 to 2008 to eradicate opium poppy in Afghanistan using aerially-sprayed chemicals damaged U.S.-Afghan relations, hindering American policy objectives in the region. The United States used USAID to implement crop substitution programs, with the objective of promoting alternative crop production such as wheat. However, such programs largely left unaccounted the potential for such inputs to be used for other means: in-kind payments of fertilizer and investments in irrigation systems designed for the growth of corn could easily be used to grow opium poppy instead. Despite the lack of success of such programs, their cost was prohibitive. In one province, Helmand, known for the active cultivation of poppy, the program costs lead adminstrators to state that if "Helmand were a country, it would be the fifth largest recipient of FY 2007 USAID funding in the world" (for Afghanistan Reconstruction, 2018).

In Mexico, policymakers are eyeing the implementation of crop substitution programs as well. In addition to proposed policies that aim to legalize opium poppy and its production for medicinal uses, current President Andrés Manuel López Obrador, has suggested that subsidies should be paid to farmers in growing regions who choose to produce corn rather than opium poppy. However, the success of such measures remains unclear – in the case of the legalization of opium poppy, Grandmaison et al. (2019) demonstrate that Mexico consumes less than 1 ton of morphine, which could legally be grown on only 321 hectares of land.

3 Related Literature

A number of papers have modeled the spillover efforts of drug production. Other work studies the factors determining criminal organization presence and points towards the prominence of spillover effects in where such groups choose to locate. Dell (2015) has found evidence that DTOs shift their smuggling routes in response to electoral outcomes in Mexico, following least-cost paths which avoid detection. In these cases, Dell (2015) finds that municipalities which experience plausibly exogenous shocks in drug enforcement shift violence elsewhere, suggesting that enforcement efforts may simply displace violence. Other work highlights the importance of supply shocks (Castillo et al. 2018) and trade (Dell et al. 2018) in causing drug related violence. Sviatschi (2017) also provides evidence that selective targeting of conditional cash transfer (CCT) programs in Peru led to spillovers of drug production into regions without those programs. In related work, Clemens (2008) examines the feasibility of reducing opium poppy supply in Afghanistan. Finally, Mejia and Restrepo (2016) models the potential spillovers of policies aimed to reduce drug production in Colombia to other producing countries, and estimates the marignal cost per kilogram of such policies.

Perhaps most related to my work is that of Dube et al. (2016), who determines a negative relationship between the price of corn in Mexico and of illicit drug seizures, indicating the plausiblity of substitution between illicit and licit drugs in this context. However, one shortcoming of the study is that it is unable to distinguish between seizures and eradications of drugs reported by the Mexican Secretariat of National Defense (SEDENA) and production of drugs (which is obviously not reported in surveys).

As drug trafficking organizations may provide a large source of employment to rural farmers in poor communities (Rios, 2008), my work relates to papers studying the sources of underdevelopment of rural areas. Such work has argued for the existence of an "agricultural productivity gap" in developing countries (Gollin et al., 2014), suggesting that labor is largely misallocated. Although various theories have aimed to explain this gap, I propose another mechanism that may be highly relevant in this context: unobserved (to data collectors) illegal drug production.

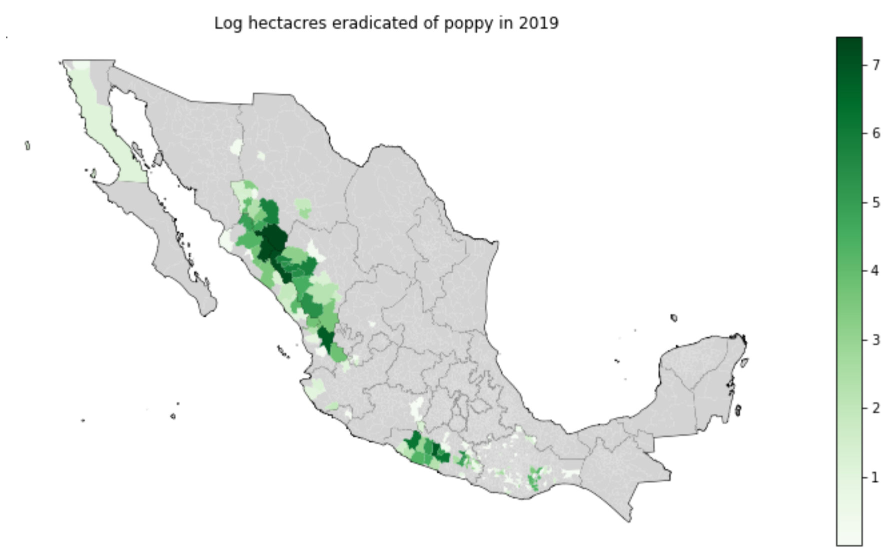
My work also relates to papers studying the labor market effects of black market employment. Sviatschi (2017), using a suitability index for cocaine similar to the index I construct, finds that children who grow up in cocaine suitable municipalities in Peru are subsequently 30% more likely to be incarcerated as adults. Khanna et al. (2019) finds that in Colombia, the availability of unemployment benefits is related to spikes in organized crime. Rios (2010) develops a model examining the factors leading workers to seek employment in the drug sector, arguing that the incentives to join legal labor markets are a crucial factor in this decision. Additionally, a wide number of papers have examined the links between drug production and insurgency. Piazza (2012) examines whether opium production in Afghanistan leads to increased incidents of terrorism and finds that provinces that produce more opium feature higher levels of terrorist attacks and casualties. In contrast, Gehring et al. (2017) use an instrumental variables strategy to determine that labor-intensive opium production reduces violence in the same setting.

On the methodological side, the theoretical model I develop is most closely related to the work of Bergquist et al. (2020) and Sotelo (2020), and the literature on how trade affects local crop allocations more broadly[2], which also guides my estimation procedure for understanding how observed price and production information inform us about the degree of substitution between licit and illicit crop production. My two tier production function is similiar to that featured in Farrokhi and Pellegrina (2020).

[2]Other papers in this literature include Allen and Atkin (2016), Costinot and Donaldson (2011), and Costinot et al. (2016), Donaldson (2018), and Fajgelbaum and Redding (2021).

4 Data

The Mexican National Institute of Statistics, Geography, and Information (INEGI) conducts the national agricultural survey (*Encuesta Nacional Agropecuaria*), which covers information regarding crop choice, input decisions, production, and sales at the farm level in 2017 and 2019. I supplement this fine-grained production survey with aggregate yearly agricultural production data from the *Servicio de Información Agroalimentaria y Pesquera* (SIAP) which provides info on crop level production and value from 2003-2019 at the municipality level. In addition, SIAP provides the same agricultural production information at the state level going back to 1980.



I couple these sources on licit crop production with several sources which provide information regarding illicit crops. I obtain information on the number of hectacres eradicated daily of opium poppy and marijuana from the Mexican Secretariat of National Defense (SEDENA, by its initials in Spanish) from 2013 to April 2021 obtained through *solicitudes de información* made in the *Plataforma Nacional de Transparencia*.[3] At the time of writing, I use the number of hectacres of illicit crops eradicated by SEDENA as a proxy of illicit crop production to produce my current estimates. I do so for the moment, with full knowledge of the limitations inherent in doing this, namely that eradications may be a biased proxy of production. Ultimately, I aim to replace this measure with that of a remotely sensed measure of opium poppy production as described in the section below, which should not be subject to similar concerns of biased targeting or selective reporting.

To obtain information on the wages and occupations of workers in Mexico, I employ the Population Censuses conducted every 5 years by INEGI which are representative at the municipality, as

[3] I also obtain information on seizures of broader types of drugs, laboratory busts, and drug related arrests through the same platform.

well as the *Encuesta Nacional de Ingresos y Gastos de los Hogares* (ENIGH), which also provides wage and spending information every 2 years, although the surveys are meant to only be nationally representative. Information on the road network of Mexico, including road length, road quality, and speed comes from the National Network of Roads (RNC) dataset provided by INEGI.

5 Remote Sensing

Since 1974, there have been efforts to detect illicit drug production in Mexico from the skies. The Mexican government and US agencies such as the CIA and DEA cooperated to monitor drug production using photographs taken from reconaissance airplanes. However, efforts were scattered and not particularly focused, and aerial photographs were rarely coordinated with eradication efforts on the ground. In recognition of the mixed success of the program, in 1983, the Mexican government divided its territory into a series of areas, in which more focused efforts could be directed towards recognizing drug production areas and eradicating illicit plantations, which were increasingly directed at areas known for the production of drugs (United Nations Office on Drugs and Crime, 2016).

This too, was limited and not always effective. As noted in a US General Accounting Office report on the bilateral U.S.-Mexico Opium Poppy and Marijuana Aerial Eradication Program to the US Congress, "numerous documents point to corruption as a problem which reduces program effectiveness. Department of State and Drug Enforcement Adminstration (DEA) officials have testified before Congress that corruption in Mexico's law enforcement organizations has had an undetermined, but certainly detrimental, effect on the eradication program and DEA noted that corruption led to tolerance of increased cultivation, which increased crop eradication requirements"[4]. Further, such efforts were costly, and were often directed only towards areas most likely to grow drugs.

Since then, the Mexican government and the United Nations Office on Drugs and Crime (UNODC) have detected the growth of opium poppies using remote sensing techniques (United Nations Office on Drugs and Crime, 2016), (United Nations Office on Drugs and Crime, 2018). Using information on the location of prior opium poppy seizures to target their efforts, the UNODC employ analysts to hand classify satelite imagery of opium poppy fields. In many cases, evidence of poppy production is confirmed through on-the-ground eradication efforts undertaken by SEDENA. However, unlike remote sensing efforts to detect drugs such as in Colombia, the method that the UNODC employs in Mexico is to take small sample regions, examine them for evidence of poppy, and then extrapolate their findings to other areas of Mexico to produce estimates of poppy pro-

[4]This is depicted in the American television series *Narcos: Mexico*, where the capture of police forces by the drug trafficking organizations prevented the dissemination of timely aerial photographs to the DEA.

Figure 2: A field of opium poppy eradicated by SEDENA on May 20th, 2020 in the municipality of Trincheras, Sonora. Source: Info Nogales, retrieved on May 24, 2020.

duction. Such extrapolations cannot provide any information about municipality (or finer) level production, such as the estimates of coca production available in Colombia, and are used mainly to provide country level estimates of total production.

Despite the limitations of pre-existing remote sensing estimates in Mexico, there has been a recent proliferation in research in the remote sensing field dedicated to remote sensing opium poppy production in other contexts. Most studies examining opium poppy production have focused on Afghanistan[5], which is the largest estimated producer of opium poppy. Examples of recent literature in this field include Taylor et al. (2010), Liu et al. (2018), Simms and Waine (2016), Simms et al. (2016), Simms et al. (2017), Waine et al. (2014), and Wang et al. (2016).

These studies highlight the feasibility of using satelite imagery to detect fields of opium poppy in Mexico. Part of the reason why remote sensing may be feasible in this context is that as visitors to poppy growning regions of Mexico note "that most of the poppy fields are not really hidden, and that most of them were visible from a considerable distance, especially when the poppy flowers were in bloom effectively covering the sierra in thousands of red dots" (Grandmaison et al., 2019).

In my work, I closely follow the method of Srinivas et al. (2004), who develop an algorithm for poppy detection based on the weighted vegetation index (WDVI). Using reflectance signatures of laboratory grown crops, Srinivas et al. (2004) find that within the last 45 days of poppy growth,

[5]To the best of my knowledge and as of current writing, no study except for the UNODC studies have attempted to remote sense poppy in Mexico.

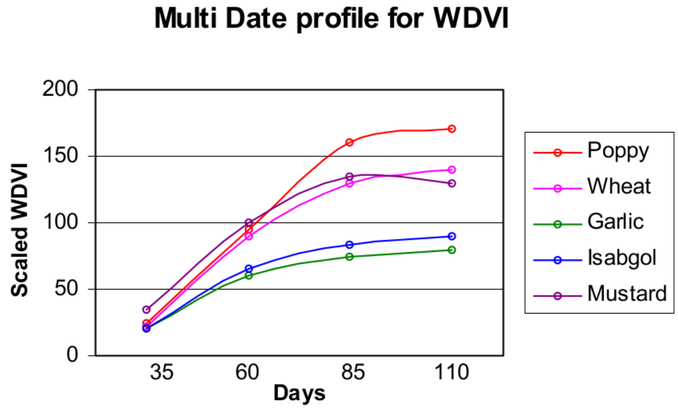
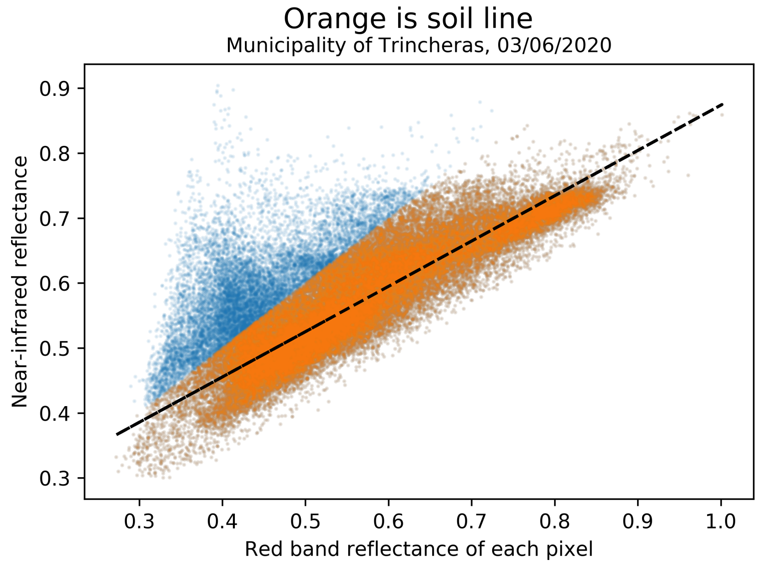


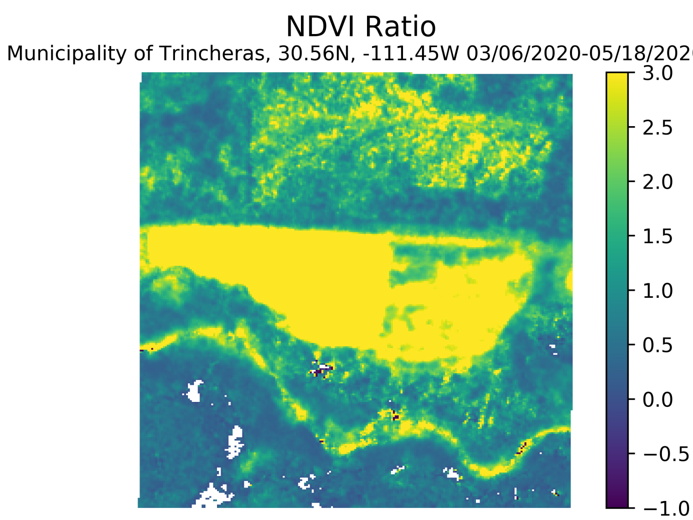
Table from Srinivas et al. (2004) showing the evolution of WDVI during crop cycle

such an index can accurately discriminate poppy from other crops (see Figure below). They confirm the usage of this index by applying their method to remote sensed satelite data which they then confirm with ground truthed GPS information. Such an index has the advantage that relies on precise rules based on the reflectance of the image to classify the growth of opium poppy, rather than black-box classifiers such as convolutional neural networks, which can certainly produce accurate classifiers but those that may rely on features of images correlated with poppy production one would like to avoid.

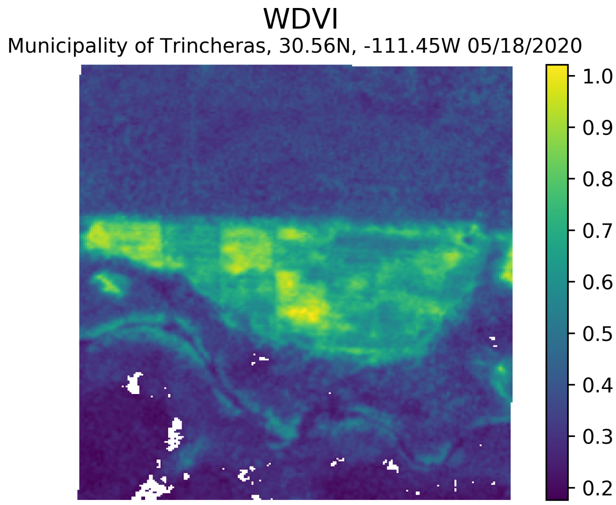
In Mexico, there are usually between two and three possible growing seasons for opium poppy. The most profilic are the periods of November-December to February-March, which is referred to as the *sereno* period, and of March to May-June, which is referred to as the *secas* period, which yields the most profitable opium. There is also another period from June-July to October-November, but this occurs during the rainy season in Mexico and usually produces the weakest opium poppy (Grandmaison et al., 2019). As such, any remote sensing strategy must incorporate the seasonality of production and evaluate all of Mexico twice or three times a year focusing on obtaining imagery of crop growth in the 45 days.



The method of Srinivas et al. (2004) involves the usage of a cloudless satellite image taken at the beginning and end of each growing season. The image taken at the beginning of the season (a so-called fallow image) is then decomposed into a scatter plot of the reflectance of each pixel in the dimensions of red band and near-infrared (NIR) reflactance. The top left part of the image contains pixels that represent vegetation, and to the bottom right are pixels that correspond to soil and rocks, referred to as the soil line. Constructing WDVI involves taking the slope of the soiline (g) and using this as weight to construct a vegetation index, defined as $WDVI = NIR - g * Red$. Then, negative values of WDVI are discarded from the search region, as these generally correspond to pixels containing water.

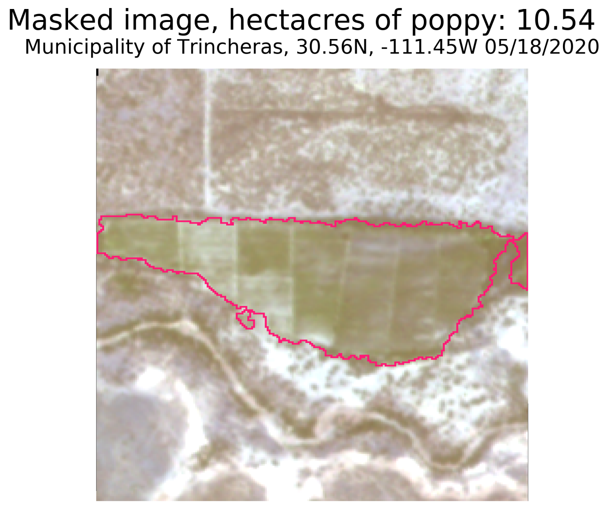


The following steps use the two images of the search area to construct a ratio of NDVI across time, which reflects the growth of vegetation in the image. Fortunately, the main growing seasons occur during the dry season, so in general I find that NDVI is usually decreasing in most of my training images. I then subset down to areas in which I see vegetation growth (where the ratio is greater than 1), in addition to subsetting down the image to remove roads and urban areas. Finally, the target area is constructed by subsetting down to areas in which the WDVI value is greater than $140/200 \approx 0.7$, the critical value suggested by Srinivas et al. (2004) for discrimination of opium poppy from other crops.



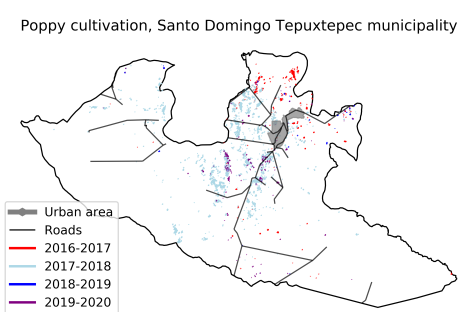
To implement this procedure, I use imagery provided by Planet Laboratories, which comes at a 3 meter resolution and has near daily coverage of Mexico (Planet Team, 2017). I display images of the workflow and output in the figures in this section. While Srinivas et al. (2004) conclude that their method yields 91% accuracy of classification, to provide validation of their method in my context, I search newspapers and Twitter for stories on eradications of fields of ilicit crops that have taken place in Mexico during the period of 2016 to the present (the period for which Planet has high quality satellite imagery). Although geolocation of many fields are difficult – some reports are suprisingly easy to find; in some cases exact geographic coordinates are provided or there are detailed location clues.

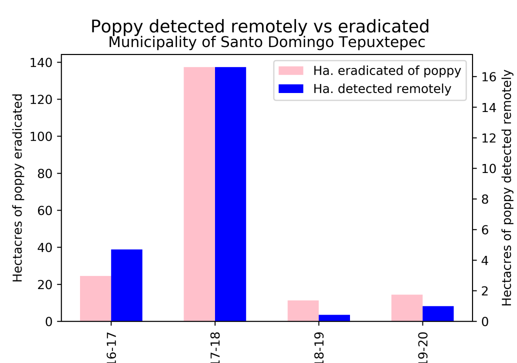
Take this story for example: "In the vicinity of the towns El Platanito and El Caimán, in the municipality of Sinaloa, the Mexican army found 6 fields of opium poppy and a greenhouse in an area of 10 ha. The fields were less than a km. from the road that goes to the town of Sinaloa de Leyva" (Mariscal, published March 23rd 2020 on debate.com.mx). The details here provide sufficient information to provide a rough area of where the fields are located, and further, upon noticing the construction and removal of a greenhouse, high confidence in finding the correct field. This procedure has been used to locate, as of writing, 15 fields of opium poppy ranging in size from 3 hectacres to 25 hectacres. As of writing, I am currently in talks with the UNODC to obtain more sample fields from Mexico and Myanmar to improve the accuracy of this algorithm, and to potentially implement a convolutional neural network (CNN) based algorithm.



Areas of the satellite image classified as opium poppy by my algorithm.

This process is still a work in progress, but the algorithm appears to do well at detecting opium poppy, especially when it is detected close to the harvest period. Eradications that occur farther from maturation of the plant have a less pronounced visible signature. However, eradications that occur close to the maturation period produce working predictions for the amount of hectacres of poppy grown in a municipality that seem to match the year-by-year fluctuations in military eradications at the municipality level quite well. Back of the envelope estimates suggest that close to 80% of the differential between opium poppy classified by our algorithm and that of eradications undertaken by the military can be explained by the timing of the satellite imagery taken: images taken after the crops have been eradicated cannot detect opium poppy. I take this as preliminary evidence that the algorithm seems to capture opium poppy relatively well.





Opium poppy detected by my algorithm versus poppy eradicated by SEDENA detected within Santo Domingo Tepuxtepec municipality, Oaxaca during the winter cultivation seasons (i.e. mid November-early December to mid-February-early March) from 2017-2020.

6 Theoretical Model

The model aims to capture the aggregate implications of changes in the supply of illegal drugs and how changes in the prices of legal goods may affect illegal drug production. The model consists of several regions, where domestic regions within Mexico are indexed as $i \in \mathscr{M} \equiv \{1, \ldots, I\}$, and $i = F$ refers to the rest of the world (ROW), modeled as one region for simplicity.

At the core, the model features a aggregate production function of a given crop which is characterized by a two-tier constant elasticity of transformation (CET) production function. An aggregate production function with a constant elasticity of transformation generates a concave production possibility frontier, allowing for varying degrees of substitutability between production of different outputs. In the first tier, I model the production of crops within a licit/illicit category. In the second tier, I model the production of crops across licit and illicit crops. By splitting the model into two tiers, I allow for different elasticities of substitution between licit and illicit crops, while maintaining the tractability of the CET production function, which imposes the same curvature of the PPF across different crops within a (il)licit crop group.

Specifically, I assume that in any given region i, land H_i can be used to produce a total quantity of legal or illegal crops Q_{ij} with legal status j with productivity $\tilde{T}_{ij}$ such that the following constraint holds:

$$\left(Q_{i,licit}/\tilde{T}_{i,licit}\right)^{\frac{1}{1-\varphi}} + \left(Q_{i,illicit}/\tilde{T}_{i,illicit}\right)^{\frac{1}{1-\varphi}} = H_i^{\frac{1}{1-\varphi}}. \tag{1}$$

Here, $\varphi > 0$ governs the elasticity of transformation between licit and illicit crop production. If φ is large, production will be skewed towards either the legal or illegal sector, depending on the productivity of the region, and we will observe larger specialization. If φ is smaller, specialization will tend to be incomplete and many regions will feature drug production. For now, φ can be less than one, but when I provide microfoundations for φ, these restrict this parameter to be greater than one, which constrains the price elasticity of supply of legal crops to be positive. This parameter reflects the institutions, police enforcement levels, and other factors which may lead to increased drug production.

In turn, in the lower tier, I assume that land allocated to either legal or illegal production H_{ij} chosen in the first step can be used for the production q_{ik} of varieties/crops denoted by k within a given legal status $j(k)$ with productivities $\tilde{T}_{ik}$ such that the following holds[6]:

[6] In the future, I will use the shorthand $k \in K_j \equiv \{k : j(k) = j\}$ to define the set of all crops of a given legal status j.

$$\sum_{k:j(k)=j} \left(q_{ik}/\tilde{T}_{ik}\right)^{\frac{1}{1-\theta}} = H_{ij}^{\frac{1}{1-\theta}}. \tag{2}$$

Similarly, $\theta > 0$ governs the elasticity of transformation between crop varieties that are either legal or illegal production. If θ is large, production will be skewed towards the most productive crop a region can grow. Again, θ for now can be less than 1, but my microfoundations eliminate this possibility later on. In contrast to φ, θ reflects inherent frictions in the substitution of crops such as learning by doing or obtaining seeds and new capital for farming. Implicitly, I assume that these "switching frictions" are the same across legal and illegal crops, i.e. it is just as difficult to switch from the production of maize to sorghum as it is from marijuana to opium poppy. This mainly provides tractability – while I have limited farm-gate price estimates for marijuana and opium poppy, I infer these prices in many areas where they are missing. This inference is likely to yield larger bias in the estimation of θ_j (were I to estimate this separately for crops of differing status) than φ, since the farm-gate prices of illicit crops are much larger than licit crops, and regional fluctuations in the farm-gate price of illicit crops are likely small compared to the absolute difference in prices between licit and illicit crops (or even compared to the yearly price shocks to illicit crop prices).

The share of land H_i allocated to the production of crop k, η_{ik}, can be represented by the product of two terms: $\eta_{ik|j}$, the share of land allocated to crop k conditional on the decision on how much total land to allocate to licit or illicit crops, and η_{ij}, the share of land allocated to licit or illicit crops. The share of land allocated to crop k, is assumed to be expressed as

$$\eta_{ik|j} = \frac{T_{ik}^{\theta}\lambda_{ik}^{\theta}}{\Phi_{ij}^{\theta}}, \tag{3}$$

where I define $\Phi_{ij}^{\theta} \equiv \sum_{l\in K_j} T_{il}^{\theta}\lambda_{il}^{\theta}$, and λ_{ik}^{θ} is a term that reflects the production cost of k. In contrast, the share of land allocated to legal or illegal crops (j) will be given by

$$\eta_{ij} = \frac{T_{ij}^{\varphi}\left(\Phi_{ij}^{\theta}\right)^{\varphi}}{\sum_{p\in\{licit,illicit\}} T_{ip}^{\varphi}\left(\Phi_{ip}^{\theta}\right)^{\varphi}}, \tag{4}$$

where I define $\Phi_{i}^{\varphi} \equiv \sum_{p\in\{licit,illicit\}} T_{ip}^{\varphi}\left(\Phi_{ip}^{\theta}\right)^{\varphi}$.

For a given set of prices, maximizing the overall value of production in a region yields that the aggregate quantity produced of crop k will be

$$q_{ik} = c_k\Phi_i\eta_{ik}H_i p_{ik}^{-1}, \tag{5}$$

where c_k is a crop specific constant, $\eta_{ik} \equiv \eta_{ik|j} \times \eta_{ij}$, and Φ_i, defined as above, corresponds to the value of a parcel of land in region i, or a producer price index.

While in the preceding section I provide the assumptions that give rise to such an aggregate production function, the equations above are sufficient to derive my main estimating equations, and with minimal additional assumptions, namely assumptions about how price shocks transmit through the trading network coming from preferences, are sufficient to derive my main general equilibrium results. For my main results to hold, then, any set of microfoundations that fulfill equations (1-5) above can be used. In particular, while I provide microfoundations similar to those in Sotelo (2020), such assumptions can be relaxed, subject to equations (1-5) holding.

Preferences I begin by presenting my assumptions about prefences, which govern the tranmission of price shocks across regions. Suppose that the utility of a worker born in region i but living in region j is given by:

$$U_i(\nu) = (1 - \tau_{ij}) C_i \varepsilon(\nu), \tag{6}$$

where C_i is a general consumption bundle. Each agent ν has a set of idiosyncratic preferences $\varepsilon(\nu)$ for living in different regions i, drawn from a Fréchet distribution with the scale parameter set to unity and a shape parameter κ. Workers in regions in Mexico can move to other destinations at a cost of $\tau_{ij}C_j$, and a worker ω in location j chooses to live in a region $j \in \arg\max_{j \in \mathscr{M}} (1 - \tau_{ij}) C_i \varepsilon(\nu)$, with $\tau_{ii} = 1 \ \forall i$.

The consumption good C_i is modeled as Cobb-Douglas over sectoral output aggregates, i.e.

$$C_i = \prod_{s \in \{A,D,M,S\}} C_{i,s}^{\beta_{is}}, \textbf{where} \sum_{s \in \{A,D,M,S\}} \beta_{is} = 1, \tag{7}$$

and $C_{i,A}$ represents agricultural consumption, $C_{i,D}$ represents narcotics consumption, $C_{i,S}$ represents consumption of nontraded services, and $C_{i,M}$ represents traded manufacturing consumption. The price index in region i is thus given by

$$P_i = \prod_{s \in \{A,D,M,S\}} P_{i,s}^{\beta_{is}}. \tag{8}$$

Consumers consume agriculture as a constant elasticity aggregate given by

$$C_{i,A} = \left(\sum_{k=1}^{K} a_k^{1/\sigma_A} C_{i,k}^{\frac{\sigma_A - 1}{\sigma_A}} \right)^{\frac{\sigma_A}{\sigma_A - 1}}, \tag{9}$$

where $\sigma_A > 0$ is the elasticity of substitution across crops, and $\sum_{k=1}^{K} a_k = 1$, with $a_K > 0$. Drugs (either heroin/opium poppy or marijuana, the two drugs I observe eradications for) are consumed as a CES aggregate, i.e.,

$$C_{i,A} = \left(\lambda_{op}^{1/\sigma_D} C_{n,op}^{\frac{\sigma_D - 1}{\sigma_D}} + \lambda_m^{1/\sigma_D} C_{n,m}^{\frac{\sigma_D - 1}{\sigma_D}} \right)^{\frac{\sigma_D}{\sigma_D - 1}}, \tag{10}$$

with $\lambda_m + \lambda_{op} = 1$.

Firms There are three industrial sectors: a representative agricultural farmer (A), nontraded services (S) and manufacturing (M). Each sector features different firms which sell their output in different markets, but all hire local factors in similar ways.

Agents In each region, there is a representative agent who owns land $\ell \in \Omega_i$ (where each plot ℓ of size one) and supplies labor L_i inelastically. Such an agent will supply $L_{i,A}$ amount of labor to the agricultural sector, $L_{i,M}$ to the manufacturing industry, $L_{i,S}$ to the nontraded services industry.

Trade In the model, trade is costly, which is modeled using iceberg trade costs. That is, for 1 unit of output in sector s to arrive in destination n from origin i, $\tau_{ni,s} \geq 1$ units must be shipped. Trade costs within a region are assumed to be zero, that is, $\tau_{ii,s} = 1$ for all regions i and sectors s. Further, I assume that trade costs are symmetric, $\tau_{ni,s} = \tau_{in,s}$ for all i, n and s, and assume that the triangle inequality holds, that is $\tau_{ni,s} \leq \tau_{nj,s} \times \tau_{ji,s}$ for all i, n, j, and s. If the sector is non-traded, i.e. if $s = S$ (nontraded services), then for all $n \neq i$, $\tau_{ni,s} = +\infty$.

Production Suppose that the production function of a crop k in region i in plot ℓ which has legal status $j(k)$ is Cobb-Douglas and given b[7]y:

$$q_{ikj(k)}(\ell) = l_{ik}(\ell)^{\alpha_{ik}} \times [t_{ik}(\ell) z_{ik}(\ell)]^{1-\alpha_{ik}}.$$

Here, l_{ik} is the amount of labor employed in plot ℓ, t_{ik} is the share of land in plot ℓ allocated to k, and z_{ik} is a productivity shifter. This productivity shifter can be decomposed into two parts: $z_{ik}(\ell) = a_{ik}(\ell) \times z_{ij(k)}(\ell)$, the first term representing the productivity of region i in producing crop k, and the second representing the productivity of the region in producing legal or illegal crops. I assume that realizations of both terms are drawn independently from the following Fréchet distributions:

$$P\left(a_{ik}(\ell) < z\right) = \exp\left(-\tilde{\gamma}_1^{\theta} T_{ik}^{\theta} z^{-\theta}\right),$$

$$P\left(z_{ij(k)}(\ell) < z\right) = \exp\left(-\tilde{\gamma}_2^{-\theta} T_{ij}^{\theta} z^{-\varphi \times \theta}\right),$$

with $\tilde{\gamma}_1 \equiv \left[\Gamma\left(1 - \frac{1}{\theta}\right)\right]^{-1}$ and $\tilde{\gamma}_2 \equiv \left[\Gamma\left(1 - \frac{1}{\varphi\theta}\right)\right]^{-1}$. For tractability, I make the following assumption: that $a_{ik}(\ell)$ is realized only after the representative landowner chooses how much land to

[7] Production in other sectors similarly (manufacturing and services) similarly employs labor and land at varying productivities, which are calibrated to rationalize domestic expenditures across various regions.

allocate to either licit or illicit crops, η_{ij}. If the area is unsuitable for crop k, the scale parameter T_{ik} is set to zero.

Then the farmer who owns plot ℓ chooses to maximize the total return to their plot[8]:

$$R(\ell) = \sum_k p_{ik} q_{ik}(\ell) - w_i l_{ik}(\ell).$$

The farmer's optimal choice of l_{ik} is given by:

$$l_{ik}(\ell) = \left(\frac{\alpha_{ik} p_{ik} z_{ik}(\ell)^{(1-\alpha_{ik})} t_{ik}(\ell)^{(1-\alpha_{ik})}}{w_i} \right)^{1/(1-\alpha_{ik})},$$

which implies that

$$R(\ell) = \sum_k l_{ik}(\ell) \left[p_{ikj} l_{ik}(\ell)^{(\alpha_{ik}-1)} t_{ik}(\ell)^{(1-\alpha_{ik})} z_{ik}(\ell)^{(1-\alpha_{ik})} - w_i \right].$$

Simplifying further yields:

$$R(\ell) = \sum_k \frac{(1-\alpha_{ik})}{\alpha_{ik}} w_i l_{ik}(\ell) = \sum_k \left[\lambda_{ik} z_{ik}(\ell) t_{ik}(\ell) \right],$$

where $\lambda_{ik} \equiv (1-\alpha_{ik}) \alpha_{ik}^{\alpha_{ik}/(1-\alpha_{ik})} w_i^{-\alpha_{ik}/(1-\alpha_{ik})} p_{ik}^{1/(1-\alpha_{ik})}$. Conditional on the realization of $z_{ik}(\ell)$, this collection of terms is linear in $t_{ik}(\ell)$, the share of land in plot ℓ allocated to crop k. Therefore, the solution is found at a corner, setting $t_{ik}(\ell) = 1$ for crop l such that

$$l = \arg\max_k \left[\lambda_{ik} a_{ik}(\ell) z_{ij(k)}(\ell) \right].$$

Conditional on the choice of how much agricultural land to allocate to licit vs. illict crops η_{ij}, then the share of land allocated to a given crop $k \in K_j \equiv \{l : j(l) = j(k)\}$ is given by equation 3 above. In contrast, the share of overall land allocated to legal crops will be given by equation 4. Given this, the unconditional probability a crop k is produced (which is also the share of land allocated to that crop by the representative farmer) is given by

$$\eta_{ik} = \eta_{ik|j} \times \eta_{ij} = \frac{\lambda_{ik}^{\theta} \widetilde{T}_{ik} \widetilde{T}_{ij} \left(\Phi_{ij}^{\theta} \right)^{\varphi-1}}{\sum_p \widetilde{T}_{ip} \left(\Phi_{ip}^{\theta} \right)^{\varphi}}, \tag{11}$$

[8]Henceforth, I drop the $j(k)$ subscript for notational clarity when it is clear.

Under these assumptions, the aggregate quantity produced of crop k will be given by:

$$q_{ik} = (1-\alpha_{ik})^{-1}\Phi_i\eta_{ik}H_i p_{ik}^{-1} = (1-\alpha_{ik})^{-1}\Phi_i^{1-\varphi}\widetilde{T}_{ij}\widetilde{T}_{ik}\lambda_{ik}^{\theta}\left(\Phi_{ij}^{\theta}\right)^{\varphi-1}H_i p_{ik}^{-1}, \tag{12}$$

which matches equation 5 by setting $c_k = (1-\alpha_{ik})^{-1}$.

With only one crop $k \in K_j$, the partial elasticity of supply is given by $\frac{\theta\times\varphi}{(1-\alpha_{ik})} - 1$, so the output of crop k is increasing in its price if $\theta \times \varphi > (1-\alpha_{ik})$. Considering that my microfoundations assume that $\theta > 1$ and $\varphi > 1$, this should always be fulfilled, but should be kept in mind for now when considering my empirical findings.

Towards finding an equilibrium

Full details and a proof of the competitive equilibrium are provided by Sotelo (2020). I provide a brief outline here. The competitive equilibrium is defined by: the set of wages in each sector $w_{i,s}$, goods prices p_{is}, consumption C_{ik} and output q_{ik} of all crops k, final goods expenditure $E_{ij,s}$, trade flows $z_{il,s}$, and labor allocations $L_{i,s}$ such that:

1. the consumer solves their utility maximization problem optimally given income and prices

2. the inputs and outputs solve the representative farmer's problem, given prices

3. agricultural goods prices are determined by the lowest cost producer, or

$$p_{nk} \leq \tau_{ni,k} p_{ik},$$

with equality if i ships k to n.

4. The labor, land, and crop markets clear in each region i.

5. Trade is balanced between Mexico and Foreign.

6. (In the version of the model with free labor mobility) Representative agents are freely mobile to choose which region to live. Given properties of the Fréchet distribution, the share of workers in region i who choose to live in region $j \in \mathscr{M}$, m_{ij}, is given by

$$m_{ij} = \frac{\left((1-\tau_{ij})w_j\right)^{\kappa} P_j^{-\kappa}}{\sum_{k\in\mathscr{M}}\left((1-\tau_{ik})w_k\right)^{\kappa} P_k^{-\kappa}}, \tag{13}$$

where I define P_i as in equation 8.

7 Calibration

In this section, I describe how I calibrate the primary parameters of interest in my model.

α_{ik} – Input shares of labor (l) and land (t)

In Sotelo (2020), the revenue share of a given crop k in a region i, π_{ik} can be expressed as:

$$\pi_{ik} = (1-\alpha_k)^{-1} \times \eta_{ik} \times c_i \tag{14}$$

where c_i is a constant that varies at the regional level and noting that here it is assumed that $\alpha_{ik} = \alpha_k \forall i, k$. Therefore, the share of land used in agricultural production expenditures, $(1-\alpha_k)$, can be recovered from estimating the equation

$$\log \pi_{ikt} = \Lambda_k + \log \eta_{ik} + \Lambda_{it} + \varepsilon_{ikt}, \tag{15}$$

where Λ_k and Λ_{it} are crop and municipality-time fixed effects respectively and I omit one base crop that I assume that uses twice as much labor (in expenditures) as land. This procedure yields an average α of 0.71. In future work, I intend to return to INEGI to use the national agricultural census to estimate input usage shares at the farm level to improve precision of these estimates.

θ – Elasticity of transformation across crops/varieties

Equation 3 implies that in any given time period t, we have

$$\log \eta_{ikt} = \theta \log \left[p_{ikt}^{\frac{1}{(1-\alpha_{ik})}} \right] - \frac{\alpha_{ik} \times \theta}{(1-\alpha_{ik})} \log(w_{it}) + \log(T_{ikt}^{\theta}) - \log(\Phi_{ijt}^{\theta}) + \varepsilon_{ikt},$$

where, to recall, η_{ikt} is the share of legal agricultural land in region i devoted to crop k, p_{ikt} is the price of crop k in region i, T_{ikt} is crop specific productivity, and Φ_{ijt} is a regional productivity index. Assume $\log T_{ikt}$ can be written as $\log T_{ik} + \log T_{state(i)kt} + \log T_{it} + \log \xi_{ikt}$, so crop-municipality specific productivity is time-invariant, and $\log \xi_{ikt}$ are "errors" in cropping decisions that are systematically uncorrelated with productivity. I estimate θ solely using information on legal crops, given the discussion in Section 6 where I address why an assumption is necessary and likely appropriate in this setting. Then, I can estimate θ without information on agricultural productivities (or wages, following the same assumption) through the usage of region-time, state-crop-time and region-crop fixed effects:

$$\log \eta_{ikt} = \theta \log \left(p_{ikt}^{1/(1-\alpha_k)} \right) + \theta \log \left(w_{it}^{-\frac{\alpha_k}{(1-\alpha_k)}} \right) + \Lambda_{i\times t} + \Lambda_{s(i)\times k \times t} + \Lambda_{i \times k} + \varepsilon_{ik,t}. \tag{16}$$

Conditional on estimates of the cost share of labor in the Cobb-Douglas agricultural production function (α_{ik}) described below, I can capture the sensitivity of within-group land share changes to agricultural crop prices, θ. I present the results of my OLS regression in Table 6. Column 1 presents the results of estimating equation 16 using OLS. The estimated coefficient for θ is almost a true zero. One reason for this may be classic simultaneity bias inherent in supply and demand estimation. Therefore, I search for an instrument that yields exogenous demand shifts in the prices of agricultural crops, which will yield a hopefully unbiased estimate of θ. To instrument for prices, I follow Roberts and Schlenker (2013) and use lagged yield shocks as an instrument for estimating supply elasticities. As Roberts and Schlenker (2013) note, the use of lagged yield shocks as an instrument is possible "because past weather-induced supply shocks affect inventories, and inventories affect the futures price in subsequent periods[, and the] key assumption for consistent identification of the supply elasticity is that past weather-induced supply shocks have zero covariance with unobserved supply shifters in the current period." The authors argue that to control for unobserved supply shifters, one should also control for contemporaneous yield shocks in the supply equation.

I present the instrumented results of such a procedure in Column 2. My estimated θ here is approximately 1.3. However, one concern is that the instrumental variables strategy of Roberts and Schlenker (2013) is intended for use only of crops that are traded internationally in markets where futures contracts are possible. My sample from SIAP includes many artisanal crops likely intended only for domestic consumption, for which well defined markets may only be present locally (at best). Therefore, in column 4, I subset my sample down to only the top 10 crops by agricultural production value in Mexico, which includes crops like maize and sorghum, storable commodities for which futures markets are well defined and Mexico is a known exporter of. Upon performing this subsetting, my estimated θ is 1.6, which is at the lower end of similar results in the literature. For instance, Bergquist et al. (2020) estimates a range of θs from 1.8-2.9, Farrokhi and Pellagrina (2020) finds 2.05, and Sotelo (2020) estimates a value most closely related to my results – 1.658.

$T_{i,k}$ – productivity of region i in growing crop k

Given estimates of θ and α_{ik}, I obtain estimates for agricultural productivity by searching for values of $\{T_{ikt}\}_{k \in K_j}$ for each municipality-year pair that rationalize equation 3 using nonlinear optimization methods and observed farm-gate prices and land shares from SIAP and agricultural wage levels from the Population Census. Such values $\{T_{ikt}\}_{k \in K_j}$ are unique up to setting one parameter equal to a constant, so in practice I set the sum of these parameters equal to a constant for each municipality-year pair. The one drawback to this approach is that any shares of land devoted to a given crop (η_{ikt}) which are observed to be zero can only be rationalized in this approach by setting $T_{ikt} = 0$. When examining counterfactuals, this implies that, for instance, any municipality currently not producing drugs will continue not to do so in the counterfactual. Other papers have emerged to address these concerns: one solution could be to estimate values of T_{ikt} using maximum likelihood as in Dingel and Tintelnot (2020), or provide some functional form which links T_{ikt} to crop suitabilities coming from FAO Global Agro-Ecological Zones (GAEZ) similarly to CDS (2016).

Figure 3: θ estimation results

Estimation of θ using only SIAP data

Dependent variable: $\log \eta_{ikt}$	(1)	(2)	(3)	(4)
$\log\left(p_{ikt}^{\frac{1}{(1-\alpha_{ik})}}\right)$	-0.000374	1.293	0.0109	1.600
	(0.00138)	(0.112)	(0.00534)	(0.494)
$\log\left(w_{it}^{-\frac{\alpha_{ik}}{(1-\alpha_{ik})}}\right)$	-0.00565	0.178	-0.0129	0.573
	(0.00311)	(0.0647)	(0.0123)	(0.350)
$\log\left(yieldshock_{ikt}\right)$	-0.0628	-0.606	-0.0604	-1.256
	(0.00351)	(0.0482)	(0.0127)	(0.369)
Mun x Year FE	Y	Y	Y	Y
State x Prod x Year FE	Y	Y	Y	Y
Mun x Prod FE	Y	Y	Y	Y
Type	OLS	IV	OLS	IV
Sample	Full	Full	Top 5 crops (wrt value)	Top 5 crops (wrt value)
N	414287	357211	55328	46655
First stage R2		0.305		0.454
First-stage/KP F. stat.		174.3		13.43

Standard errors in parentheses

Notes: Estimated using robust SEs.

The difficulty remains of how to estimate productivities of illicit crops. To make progress in this respect, I use a variety of news reports and interviews to provide information on the farm-gate prices of marijuana and opium poppy in several municipalities of Mexico. Under the assumption that all domestically produced illicit crops are exported to the United States and is sold competitively, then the price of say, opium poppy, produced in a municipality i should be given by $p_{US,opiumpoppy} = d_{US,i,opiumpoppy} p_{i,op}$. Of course, the trade costs $d_{US,i,opiumpoppy}$ for any source region could vary widely. As such, I suppose that $d_{US,i,opiumpoppy} = \lambda_d \times \text{EffectiveDistance}(US, i, k \in K_{legal})$, where λ_d is the additional cost smugglers face due to law enforcement, smuggling expenses, etc. My implied estimates for λ_d range from 33.5 to 67.46, with a mean of 58.79. In this manner I am able to predict farm gate prices of opium poppy to other regions and other time periods. I then solve for values of $\{T_{ikt}\}_{k \in K_j}$ in a similar manner to before.

φ – elasticity of transformation between licit and illicit crop production

With these estimates in hand, I proceed to the estimation of equation 4 of my model. The model implies that in any given time period t, we have

$$\log \eta_{ijt} = \log(\widetilde{T}_{ijt}) + \varphi \log(\Phi_{ijt}^{\theta}) - \log\left[\sum_p \widetilde{T}_{ip}\left(\Phi_{ip}^{\theta}\right)^{\varphi}\right] + \varepsilon_{ikt},$$

the estimation of which would require the values of illicit vs. licit crop productivity $\widetilde{T}_{ijt}$. To make progress on the estimation of this equation, therefore I estimate the model in differences between the share of licit and illicit crops.

In differences, equation (4) implies that in any given time period t, I have

$$\log \eta_{i,legal,t}/\eta_{i,illegal,t} = \varphi \log \Phi^{\theta}_{i,legal,t}/\Phi^{\theta}_{i,illegal,t} + \varphi \log(T_{i,legal,t}/T_{i,illegal,t}).$$

Recall that Φ^{θ}_{ij} is a weighted sum of the local crop prices p_{ik}, for all $k \in K_j$: so if I define $\psi_{ik} \equiv \left[T_{ik} w_i^{-\frac{\alpha_{ik}}{1-\alpha_{ik}}} g(\alpha_{ik})\right]^{\theta}$, then the productivity index in either licit or illicit crops can be written as $\Phi^{\theta}_{ij} = \sum_{l \in K_j} \psi_{il} p_{il}^{\theta/(1-\alpha_{il})}$. This can now be interpreted as follows : the relative share of legal crops grown is determined by appropriately weighted sums of prices of all legal and illegal crops.

Above, I have information on land shares and I can construct the productivity indices for either legal or illegal crops, but I cannot assemble a proxy for the ratio of licit to illicit crop productivity, $T_{i,legal,t}/T_{i,illegal,t}$, so this term enters in the error term. To avoid omitted variable bias driven by this term, I propose an instrument based on a natural experiment – the rise of fentanyl in the United States caused the farm-gate price of poppy to fall almost four-fold from 2017 to 2018, anecdotally causing farmers to shift into legal crops and to migrate elsewhere. Therefore, my instrument is a weighted sum of international prices for crops/price decrease for poppy (marijuana) driven by fentanyl (legal marijuana) during the period, where weights are $\in$ {lagged weights,current weights, weights with T_{ik} from FAO suitabilities}.

In Figure 6, I present the results of this procedure. In columns 2-4, I present results using my instrumental variables strategy where my weights are current weights, and in columns 5-7 I present results using my instrumental variables strategy where my weights are lagged (i.e. from one year prior) weights. Using lagged weights, I calculate my estimated φ to be 0.333. Of course, this value is low; with a small enough α_{ik} it is possible that the price elasticity of supply of a given crop k will not be positive. In future work I will likely try to think further about this estimation procedure: sources of mismeasurement and potential solutions such as instrumental variables.

With these results in hand (for now I assume $\varphi = 2$ in my model results), I use my estimated $\hat{\varphi}$ to solve for $T_{ijt}(\hat{\varphi})$ in a similar manner to before. [9]

$\tau_{ni,S}$ **– Iceberg/ad-valorem trade costs** To calculate the value of ad-valorem trade costs in my setting, I closely follow Donaldson (2018) and take a good in Mexico which is relatively highly exported. Particularly, I examine red tomatoes for which $\approx 70\%$ of production is exported during

[9] In future work, with estimates of $\widetilde{T}_{ij}$ and φ in hand, I can go backwards and examine a year for which I have farm-gate estimates of opium poppy prices for several villages from the fieldwork of Grandmaison et al. (2019). Such prices for opium poppy, in addition to the productivity estimates of licit crops, allow for estimates of $\widehat{\eta}_{ijt}$, or the share of land allocated to illicit crops back in time when satellite images are not easily available.

Figure 4: Estimation of φ

Dependent variable: $\log \eta_{i,illegal,t}/\eta_{i,legal,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log \Phi^{\theta}_{i,illegal,t}/\Phi^{\theta}_{i,legal,t}$	-0.0244***	0.146***	0.152***	0.0542***	0.344***	0.333***	0.0448*
	(0.00436)	(0.0143)	(0.0147)	(0.00607)	(0.0556)	(0.0527)	(0.0227)
Mun FE	Y	N	N	Y	N	N	Y
Year FE	Y	N	Y	Y	N	Y	Y
Type	OLS	IV	IV	IV	IV w/ lag weights	IV w/ lag weights	IV w/ lag weights
N	6963	5819	5819	5486	3883	3883	3691
First stage R2		0.519	0.519	0.519	0.0786	0.0786	0.0786
First-stage/KP F. stat.		2380.0	2121.8	6156.3	135.2	143.4	227.0

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Estimated using OLS with robust SEs.

my time period, and for which more than 90% of exports are destined for North America. Furthermore, many different regions of Mexico produce and export tomatoes, which is not the case for other highly exported goods such as cocao and coffee.

Examining trade data from the US Census Bureau, I find that 97% of American tomato imports from Mexico pass through five southern border crossings: Nogales, Arizona, Laredo, Texas, Hidalgo, Texas, Otay Mesa, California, and El Paso, Texas. Given the relative simplicity of the geography of Mexican tomato exports[10], I construct a measure of effective distance of transport network based on information from the National Network of Roads (RNC). To do so, let a road/edge be given by e and the effective distance of that edge be given by $t(e)$, where $t(e) = \left(\frac{maxspeed=110}{speed_e}\right) \times length_e \times surface_e$. If the road is paved, I set $surface_e = 1$, and if dirt, I set $surface_e = 5$. Letting p denote a given path, $E(p)$ the set of edges that path comprises, and $\mathscr{P}_{ni}$ denote all feasible paths between region i and region n, the total effective distance is given by

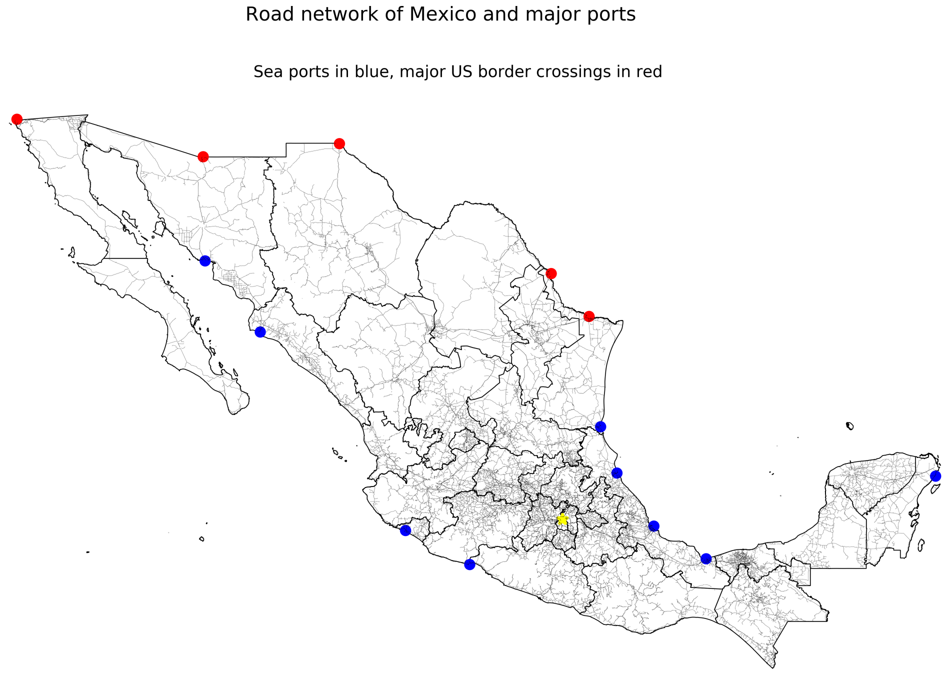
$$\min_{p \in \mathscr{P}_{ni}} t(p) = \min_{p \in \mathscr{P}_{ni}} \sum_{e \in E(p)} t(e).$$

To obtain $\tau_{ni,S}$, I calculate the effective distance for each tomato exporting municipality in the 2007 Agricultural Census to the closest U.S./Mexico border crossing. Noting that the highest prices for (exported) tomatoes are generally observed in the municipality/city of Ensenada, which is close to the U.S.-Mexico border in San Diego/Tijuana, I run the following regression:

$$\log(p_{Ensenada,tomato,t}/p_{i,tomato,t} - 1) = \beta_0 + \beta_1 \log effective distance_{ClosestBorder,i} + \varepsilon_{it}. \quad (17)$$

[10] Red tomatoes being a crucial distinction here – green tomatoes or tomatillos being much less exported and much more highly consumed domestically.

Figure 5: Visualization of National Network of Roads



I present the results below. In columns 1 and 2, I obtain that the distance coefficient is negative, the opposite as what would be predicted by theory. However, such farms in such municipalities may not be exporters and producers who supply domestically, and so distance to the United States border would logically not affect their prices. Subsetting the data to include only exporting municipalities and examining my preferred specification in column 4, I obtain $\widehat{\beta}_0 = -1.418$ and $\widehat{\beta}_1 = 0.151$, which doesn't assure $\tau_{ni,S} \geq 1$, so I set it to 1 if not. I extrapolate these estimates to calculate trade costs in the whole of Mexico using the formula $\tau_{ni} = \exp(\beta_0 + \beta_1 \log \text{effective distance}_{ni})$.

Other Parameters σ_D – Elasticity of substitution across varieties of illicit drugs

Of course, I lack concrete information about the consumption of drugs required to estimate $\sigma_D > 0$, so instead I target the own price elasticity of heroin using the estimates taken from a meta-review by Gallet (2014) and the estimated market shares of marijuana and heroin in the United States from a 2019 RAND study (in 2014, roughly $\lambda_{op} = 0.44$) (Midgette et al., 2019). Doing so yields $\sigma_D = 0.1$. With such a σ_D, the implied own price of elasticity of marijuana is higher than the meta-review suggests it would be, but is in line with estimates looking at black market consumption of marijuana alone, the relevant market here (Ruggeri, 2013).

σ_A – Elasticity of substitution across varieties of licit crops

In future work I aim to estimate elasticities of substitution using the National Survey of House-

Figure 6: Effective distance regressions

Dep var: $\log(p_{Ensenada,tomato,t}/p_{i,tomato,t}-1)$	(1)	(2)	(3)	(4)
log effective distance$_{ClosestBorder,i}$	-0.0950***	-0.187***	0.222***	0.151**
	(0.0199)	(0.0194)	(0.0518)	(0.0502)
Constant	1.377***	3.197***	-2.853***	-1.418*
	(0.281)	(0.275)	(0.719)	(0.698)
Observations	16310	16310	1716	1716
R^2	0.002	0.216	0.021	0.233
Season FE	N	Y	N	Y
Sample	Full sample	Full sample	US exporting muns	US exporting muns

Standard errors in parentheses
* (p¡0.05), ** (p¡0.01), *** (p¡0.001)

Notes: Estimated using OLS with robust SEs.

hold Income and Expenditures (ENIGH), but for now I use $\sigma_A = 2.3$ as in Sotelo (2020).

σ_M – Elasticity of substitution across traded manufacturing goods

I use an estimate of 9 from Allen and Arkolakis (2014).

$(\beta_{iA}, \beta_{iD}, \beta_{iM}, \beta_{iS})$ – Cobb Douglas sectoral expenditure shares

I calibrate aggregate agricultural spending from production and trade data using the identity $Q - X + I$. Drug expenditures from 2019 RAND study in the US. In my current results, I will assume Foreign is sole consumer of drugs to shut down potential domestic utility gains from drugs. For shares of expenditure on traded manufactured goods, I target information on output from domestic product tables. Nontraded sectoral spending is chosen to match whatever remains of domestic GDP.

a_k – consumption shares of crops k at the national level

As before, I calibrate aggregate agricultural spending on individual crop varieties using production and trade data[11] using the identity $Q - X + I$.

κ – elasticity of migration to income

I take this parameter directly from the literature. As of now, I assume that the population in each region i is fixed and will loosen this assumption in future work.

[11] I match individual commodities in the production data using a correspondence between commodities and trade data from Fally and Sayre (2018). Sometimes, I am forced to aggregate commodities in the production data to match the trade data, in which cases I divide the aggregated expenditure share into smaller variety-specific expenditure shares based on their production values.

8 Results

Here, I present the results of my model, to counterfactual simulations in both partial and general equilibrium. I begin by making the following simplifications: I assume $\theta = 1.6$ and $\varphi = 2$ (which is currently higher than what I have estimated), I restrict the set of legal crops to {Avocados, Beans, Corn} and include only opium poppy as an illegal crop, I also restrict the set of municipalities to the 1,057 municipalities that have ever produced poppy (i.e. for whom $T_{i,poppy} > 0$), and finally I shut down domestic consumption of drugs, so only ROW consumes drugs.

The main policy I consider is a subsidy to price of legal crops, in particular maize. Recently arrested ex-defense chief Salvador Cienfuegos has proposed a price floor of 3,500 pesos per ton of maize, roughly double the price of maize in rural regions, other governors of states have proposed up to 15,000 pesos per ton (Telediario, 2018). Reflecting the wide range of subsidies proposed to maize, I consider only a 10% subsidy to maize, but can simulate other, larger subsidy values as well.

To begin, I present the results of such a subsidy to maize alone in partial equilibrium. However, this does **not** consider any GE effects or changes in factor prices and holds all parameters constant. Examing only the partial equilibrium effects of such a subsidy includes can be instructive in understanding where the general equilibrium effects affect the results and to what magnitude. As in Dekle et al. (2008), I use the notation of exact hat algebra to rewrite the equilibrium conditions of the model in terms of changes relative to the baseline observed equilibrium. For instance, in this notation, $\hat{Z} = Z'/Z$ denotes the relative change, and Z' refers to the value in the new equilibrium.

Recall that aggregate output of crop k is given by:

$$q_{ik} = (1-\alpha_{ik})^{-1}\Phi_i^{1-\vartheta}T_{ik}^{\theta}T_{ij(k)}^{\vartheta}\lambda_{ik}^{\theta}\left(\Phi_{ij(k)}^{\theta}\right)^{\vartheta-1}H_i p_{ik}^{-1}.$$

Then, in terms of changes, the change in the aggregate output of crop k is given by:

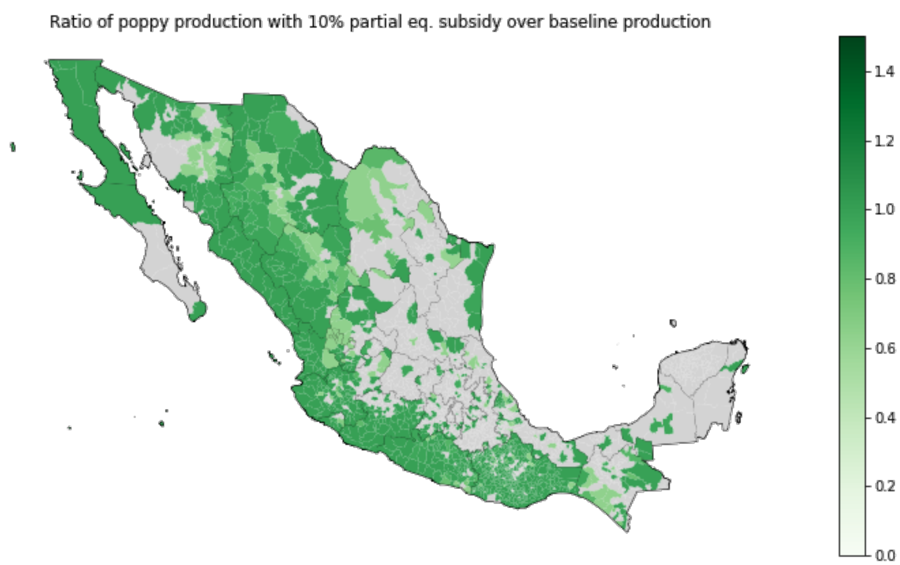
$$\widehat{q_{ik}} = \widehat{\Phi_i^{1-\vartheta}}\,\widehat{p_{ik}}^{\frac{\theta}{(1-\alpha_{ik})}}\left(\widehat{\Phi_{ij(k)}^{\theta}}\right)^{\vartheta-1}\widehat{p_{ik}}^{-1}. \tag{18}$$

This change in the aggregate output formula can be further simplified if we assume there to be only two crops, maize and opium poppy, and we examine the effects of a change in the price of maize on the output of opium poppy.

$$\log\widehat{q_{i,poppy}} \approx -\varphi\eta_{i,licit} - \varphi\log\eta_{i,corn|licit} - \frac{\varphi\theta}{(1-\alpha_{ik})}\log s$$

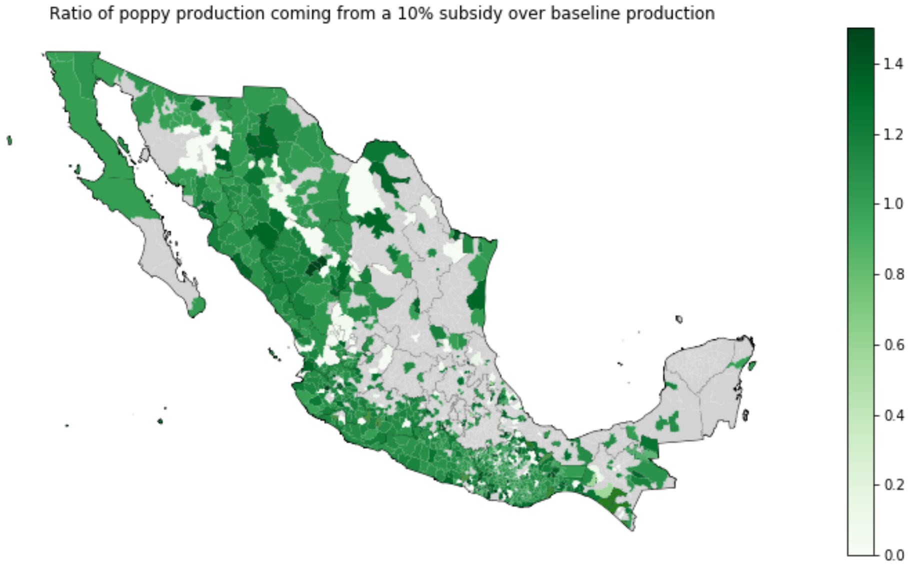
In Figure 8, I present the results of a 10% subsidy to maize alone in partial equilibrium to the net change in poppy production (the ratio of new production to old production without a subsidy).

Figure 7: Partial equilibrium results of subsidy



Ratio of poppy production coming from mutliplying the baseline values of prices from my model by $s = 1.1$ over production in baseline model (i.e. a 10% subsidy) in partial equilibrium. Average reduction in poppy production is 5.56% for a municipality. Total quantity produced of poppy decreases by 0.3%. Maximum ratio for any municipality: 0.99973. Assumes $\varphi = 2, \theta = 1.5$.

Figure 8: General equilibrium results of subsidy



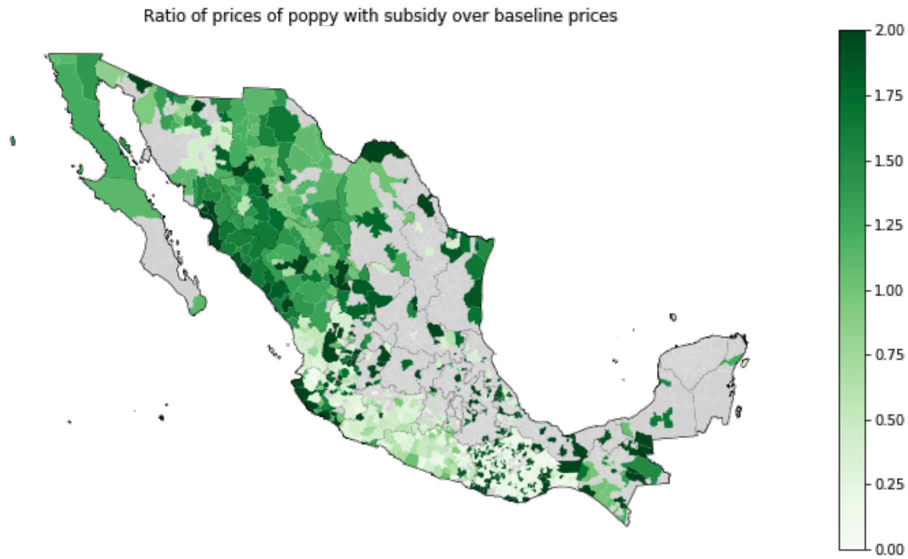
Ratio of poppy production coming from running a subsidy of $s = 1.1$ through my model over production in baseline model (i.e. a 10% subsidy). Average reduction in poppy production for a municipality is 14.55%. Maximum ratio for any municipality: 4.156. Assumes $\varphi = 2, \theta = 1.6$.

It is worth noting that many municipalities produce neither poppy in the baseline or in the counterfactual. This is because in order to justify any observations of municipalities without any observed poppy production, my calibration procedure sets $T_{i,illicit} = 0$. This has strong implications for the counterfactual exercises, since any change in policies will continue to yield zero poppy production with this parameter set to zero.[12] In my results, I find that all municipalities uniformly reduce their production of poppy as a result of the 10% subsidy on maize, on average by roughly 5.5%. As to be expected, no municipality increases its production of poppy in response to the subsidy.

Moving on to Figure 8, the results of a 10% subsidy to maize alone in general equilibrium equilibrium to the net change in poppy production (the ratio of new production to old production without a subsidy). Relative to my results in partial equilibrium, I find larger average reductions in poppy production due to the price subsidy, on average each municipality reduces its poppy production by 14.55%. However, this masks substantial heterogeneity, as I now find that there are many municipalities which increase their production of poppy in response to the subsidy. In particular, I find that most of the reductions in poppy production are driven by municipalities

[12] In the future, I hope to relax this, mostly through the use of remote sensed observations of poppy production. Such measures will inevitably feature some noise in poppy detection (the work of Srinivas et al. (2004) suggests the signal to noise ratio is fairly high, but obviously there will be many errors), resulting in estimates of poppy production likely for most municipalities. Such municipalities will have small, but non-zero values of $T_{i,illicit}$, resulting in plausible counterfactual results.

Figure 9: General equilibrium results of subsidy on farmgate poppy prices

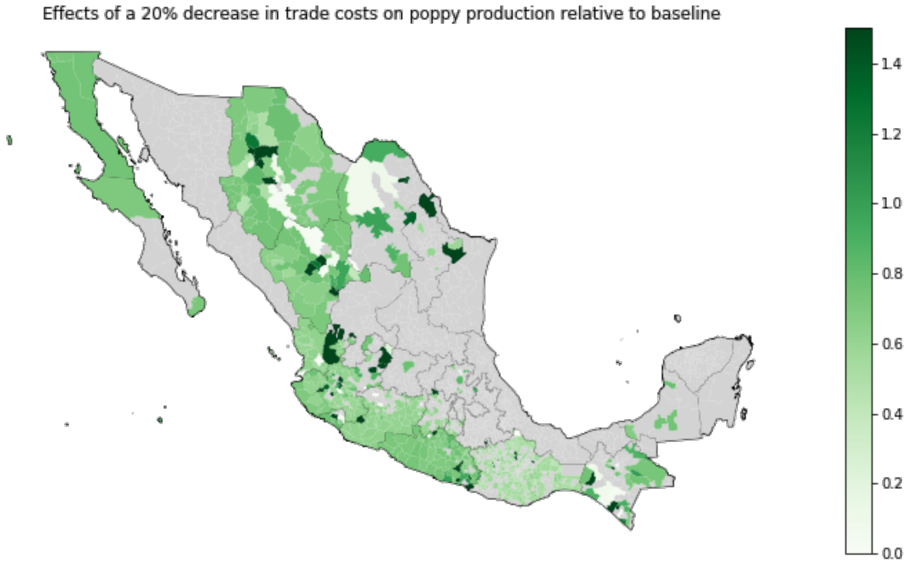


Ratio of prices in poppy coming from running a subsidy of $s = 1.1$ through my model over prices in baseline model. Assumes $\varphi = 2, \theta = 1.6$.

further away from the United States, and most of the increases are driven by municipalities with better market access to the United States. The reason for this is as follows – when maize becomes more profitable, the opportunity cost to produce it increases, shifting production towards maize and away from poppy. But given the low elasticities of demand for poppy, this yields an increase in the prices of opium poppy. In particular, these increased prices are transmitted more saliently to regions that have lower trade costs in drugs with the United States, as is shown in figure 8.

Of course, through the lens of my model I can examine other policies and their impact on opium poppy production in Mexico. For instance, I can simulate a reduction in trade costs through the lens of my model and examine the impact of increasing farmer market acess on poppy production. This allows me to compare and contrast the costs of a subsidy program to the costs of improving roads, for example. I present my results in Figure 8. The results of such a policy are mixed. On the whole, many municipalities (more than half, 667/1057) switch from producing poppy to producing much more profitable legal crops, generating larger reductions than coming from a subsidy program. However, a smaller number benefit from the reduced overall supply of poppy; they can now exploit the reduced trade costs (and higher prices for the crop) to sell substantially more poppy. On average, thus this policy increases average poppy production by $\approx 11.76\%$. In the future, I will examine other counterfactual policies to examine their effects on poppy production.

Figure 10: General equilibrium effects of 20% in τ_{ij} for all goods



Ratio of poppy production from a model in which trade costs have been reduced by 20% uniformly across regions and goods over production in baseline model. Average increase in poppy production is 11.76%. Average reduction in poppy production for the 667/1057 municipalities that reduce drug production is 40.68%. Assumes $\varphi = 2, \theta = 1.6$.

9 Concluding remarks

In this paper, I focus on the hypothetical effects of crop substitution programs implemented in Mexico. To bring new light on the scale and scope of illicit drug production in the country, I develop a large scale remote sensing algorithm to detect drug production, which allows for new questions to be answered in this setting. I estimate elasticities of crop substitution to empirically evaluate the plausibility of subsitution between crops in such a setting, and conclude that the elasticities are rather low, indicating that successful subsidy policies will be costly. Finally, I develop a model to understand what prices would give rise to reductions in illicit crop shares, and what potential "balloon" effects would arise from such a policy. In future work, I intend to compare the welfare effects of crop substitution programs to the effects of eradication programs.

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