

# THE IMPACT OF ORGANIC AGRICULTURE ON INTERNATIONAL MIGRATION: LESSONS FROM THE COFFEE SECTOR\*

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## Abstract

Can the increase in demand for organic certified products in developed countries be one of the causes of emigration from developing to developed countries? I hypothesize that the expansion of organic farming, due to organic certifications, in export-oriented agriculture sectors in developing countries made crops more vulnerable to infectious plant diseases. Consistent with the hypothesis of a negative income elasticity of emigration, the spread of the disease created an unexpected negative income shock to producers and a push factor to migrate towards more developed countries. I empirically investigate this research question by studying the coffee leaf rust (CR) epidemic that hit coffee producers in Central America in 2012/13. I find causal evidence in Guatemala by leveraging an IV strategy, that exploits the variation in distance of coffee farms to the first "as good as random" wave of organic certified cooperatives in the country, assuming that the diffusion of organic certifications happens by word of mouth. I find that a 1 SD increase in the share of organic farms in a given municipality led to 40% increase in the infection rate from CR and a 50% increase in the emigration rate in the same municipality. This evidence suggests that national organic programs and certification bodies should inform farmers about the possible unintended negative economic consequences of organic agriculture.

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# 1 Introduction

Over one billion individuals emigrated from developing countries to more developed countries between 2010 and 2020 (World Migration Report 2020). This sizable structural transformation has become of national interest in most European countries and the USA and debates on reducing migration have turned into a major political issue. Many possible push factors of emigration have been suggested, such as the ease of liquidity constraints in emerging markets, the increase in crop failure and famine, as well as the expanded network of migrants. In this paper, I propose a new - and rather counterintuitive - reason: the increased demand by consumers in developed countries for more environmentally friendly products, particularly for those imported from developing countries.

Sales of certified organic commodities increased in the past two decades by double digits in most developed countries<sup>1</sup>. Built on the foundational idea of no synthetic agrochemicals, organic certification bodies, such as USDA Organic and European Organic Certifiers Council (EOCC), provide a system of control and enforcement to guarantee that organic rules and regulations are being followed properly throughout the value chain. Although this body of rules substantially aims to improve farming soil health and to increase biodiversity, it does not specifically intend to help producers by improving their social and economic standards. The economic impact of organic farming on producers in developing countries is, therefore, dubious and theoretically can have an impact on migration flows. On the one hand, organic producers might increase their profits relative to conventional producers, ease the liquidity constraints and emigrate more likely to high income countries, suggesting a positive income elasticity of emigration. On the other hand, organic producers might be economically worse off, due to an increase in exposure to plant diseases and lower yields, suggesting a negative income elasticity of emigration.

This paper provides the first empirical analysis of whether and how the increase in demand for organic certified products in developed countries might be one of the causes of emigration from developing to developed countries. I answer two main questions: Are organic certified farmers in developing countries more likely to emigrate? If so, is this effect due to a positive or a negative income shock?

I empirically investigate these research questions by focusing on the coffee sector in Central America. There are three major reasons for this decision. First, the coffee sector

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<sup>1</sup>USDA NASS, 2019 Organic Survey (2017 Census of Agriculture).

provides an excellent setting to study these questions as (1) production happens mostly by small-holder farmers in vulnerable developing countries while consumption happens largely in developed countries, as shown in Figure 9 in appendix, and (2) organic farmed coffee areas worldwide have increased up to five-fold in the past two decades<sup>2</sup>. Second, Central America has shown in the recent years a stark increase in migration flows. As shown in Figure 18 in appendix, the major destination of emigrants from countries like Guatemala is the United States of America, chosen by more than 85% of the emigrant population. USA border officials and international organizations reported as well a huge spike in the number of emigrants from the Central America's Northern Triangle<sup>3</sup>, which comprehends Guatemala, Honduras and El Salvador (US CBP Report 2018, UNHCR Report 2015). Lastly, the coffee sector in Central America was hit in 2012/2013 by the coffee leaf rust, the most dangerous and known disease that attacks coffee plants. During the 2013 harvest season 70% of coffee plantations were affected and the national coffee production decreased by 17% compared to 2011/2012<sup>4</sup>. As organic farmers are more prone to this disease due to a lack of preventive chemical pesticides, organic agriculture might have actually accelerated the spread of the disease, and provided an unexpected negative income shock to farmers.

As the decision of a farmer to become organic can be due to unobservable characteristics correlated with the decision to emigrate, such as risk aversion and expectation of future earnings, I exploit the arrival of organic certifications in Central America as an exogenous shock to retrieve causality. Specifically, I use an Instrumental Variable strategy that exploits the cross-sectional variation in distance of coffee farms in Guatemala to the first wave of organic certified cooperatives. The intuition is that the closer a farm is to the first organic certified cooperatives, the more likely it is exposed to the news of the emerging agricultural technology by word of mouth, the more likely it joins organic farming. This hypothesis was confirmed by several focus groups that I ran in the field in December 2021<sup>5</sup>. I show that the instrument has a strong first stage, it is as good as random, and I provide suggestive evidence that the exclusion restriction holds.

One major contribution of this project is the creation of two novel datasets. First,

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<sup>2</sup>FiBL, The World of Organic Agriculture - Statistics and Emerging Trends 2022; Link

<sup>3</sup><https://www.pewresearch.org/hispanic/2017/12/07/rise-in-u-s-immigrants-from-el-salvador-guatemala-and-honduras-outpaces-growth-from-elsewhere/>

<sup>4</sup>International Coffee Organization [https://www.ico.org/new\\_historical.asp](https://www.ico.org/new_historical.asp)

<sup>5</sup>A summary of the data collected with surveys and focus groups can be seen in Figure 11 in appendix.

I personally collected data on all the coffee cooperatives in Guatemala in the past 20 years. In this dataset I have the following information for each cooperative: location, founding date, whether and when it has received any certification. This dataset allows me to retrieve the geographical variation of the first organic certified coffee cooperatives in the country, which I then use to compute the instrumental variable, i.e. the average distance from the centroid of the coffee farms in each municipality to the closest first organic certified cooperatives. Second, I use machine learning techniques and multispectral satellite data to create a national representative map of the intensity of coffee rust in the coffee plantations. I use a national representative survey of the spread of coffee rust run by the national coffee association as ground truth to train a random-forest model, that exploits the fact that coffee rust can be easily detected in the near-infrared region of the electromagnetic spectrum. This dataset allows me to assess whether areas with more organic farming are also more exposed to the disease.

I find that a 1 SD increase in the share of organic farms in a given municipality led to a 3.3 p.p. increase in the emigration rate in the same municipality, which corresponds to a 50% increase relative to the baseline. I also report a decrease in the age at migration, suggesting a deeper and more structural transformation in migration flows. I show that these results are robust to variations in the arbitrary thresholds used to define the sample and the instrument. I provide several placebo tests by focusing only on urban areas, on the period before the coffee rust arrived, and on municipalities where coffee is not produced. I then focus on the mechanisms and I use machine learning techniques and multi-spectral resolution satellite data to create a map that shows the intensity of CR over each municipality area. I find that a 1 SD increase in the share of organic farms in a given municipality led to 40% increase in the infection rate from CR. Overall, this suggests that organic farms are indeed more prone to plant diseases and it provides suggestive evidence of a negative income elasticity of migration. Further analysis on the income effect for producers is, however, still in progress. This evidence suggests that it is crucial - especially for national organic programs and certification bodies - to understand whether organic farming can have noticeable economic and structural consequences, and to balance out the environmental and the economic impacts.

This study contributes primarily to our understanding of the determinants of international migration and the role of income heterogeneity. The literature has shown

that the income elasticity of migration varies based on wealth (Bazzi 2017; Angelucci 2015; Bryan, Chowdhury, and Mobarak 2014; Clemens 2014; Bertoli, Moraga, and Ortega 2013; Facchini and Mayda 2009; McKenzie and Rapoport 2007). Intuitively, as income decreases emigration might increase due to lower opportunity costs of migrating or it might decrease due to higher liquidity constraints. This study reports that the first channel seems to prevail in a rural agricultural setting in a developing country. This study contributes also to our understanding of the economic and social impacts of ethical certifications on producers. Most of the studies that conducted a cost-benefit analysis focused exclusively on the price premium, the change in productivity, and the direct investments provided by the certification bodies (Dragusanu and Nunn 2018; Hagggar et al. 2017; Chiputwa, Spielman, and Qaim 2015; Beuchelt and Zeller 2011; Bacon et al. 2008). Many of these studies find an overall null effect, others find positive effects depending on the specificity of the type of certification. I hypothesize in this paper that the spread of plant diseases, by reducing yields, is a new channel through which organic certified producers can be economically negatively affected. This paper contributes also to our understanding of the causes of plant disease epidemics. Most of the empirical evidence focuses on the meteorological and climatic factors (Pham et al. 2019; Avelino et al. 2006), with only a few papers hinting towards the role of organic farming techniques (Avelino et al. 2015; Avelino, Willocquet, and Savary 2004). This is the first study to causally estimate the role of organic farming in the onset of plant disease epidemics.

The remainder of the paper is organized as follows. Section 2 provides some background information on the coffee sector in Guatemala, the coffee rust, and the role of organic certifications. Section 3 presents the data used in the analysis. In section 4 I describe the identification strategy in detail. Sections 5 to 6 present the main results on emigration. Section 7 discusses the possible mechanisms and section 8 concludes with possible policy implications.

## 2 Context

**The Coffee Sector** The majority of coffee in Guatemala is grown by small-holders: 96% of farmers cultivate less than 3 hectares of land<sup>6</sup>. Due to the rugged topography of the

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<sup>6</sup>Guatemalan National Coffee Association (Anacafé): <https://www.guatemalancoffees.com/main/impact>

region, harvesting is extremely difficult to mechanize and, therefore, very labor-intensive. Consequently, 10% of the total active labor force in Guatemala is connected to the coffee sector, contributing to 3.4% of the national GDP<sup>7</sup>. One of the major transformations that these coffee farms experienced in the past two decades is the expansion of organic farming: since 2004 organic farmed coffee areas worldwide have increased five-fold, and Central America's market share today represents 45% of total organic coffee trade<sup>8</sup>. In Guatemala, as of 2015, a not negligible 8% of total coffee cultivated areas is dedicated to organic farming<sup>9</sup>.

**Organic Certifications** One factor that facilitated the expansion of organic farming in recent years is the increased demand by consumers in developed countries for organic certified products. Given that most producers lack the knowledge to interpret the country-specific requirements to obtain an organic certification label, local authorized certifying agencies appeared in many producing countries to fill this gap. The deal between the certifiers and the producers can be simplified as follows: growers are promised a price premium on the selling price (on average +25%), which offsets the reduced productivity and yield (on average -40%) dictated by the avoidance of synthetic chemical pesticides and fertilizers (Donovan and Poole 2014). It is worth noticing that, in many cases, the actual certification is given to the cooperatives, to whom most of the small producers belong. The certified cooperatives then have the incentive to push all their members to switch to organic farming, because members use only one common processing mill in the cooperative, and organic and not-organic coffee must be processed separately.

**Disease Prevention** Although formally banning conventional synthetic pesticides, organic certifiers allow growers to adopt alternative methods for disease control, the most popular of which among coffee producers is the application of organic copper-based fungicides. These pesticides are notoriously more environmentally friendly, as they do not build up in water and soil. However, given that they can become toxic if applied in high doses, they are usually applied post-infection, after 10/20% of plants are infected (Merle et al.

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<sup>7</sup>World Development Indicators, World Bank (2020) <https://datacatalog.worldbank.org/dataset/world-development-indicators>

<sup>8</sup>FiBL-IFOAM-SOEL Survey (2006/2019) <https://orgprints.org/id/eprint/35385/1/FiBL-2019-Crops-2017.pdf>

<sup>9</sup>FAO Statistical Pocketbook Coffee (2015) <http://www.fao.org/3/i4985e/i4985e.pdf>

2020). Considering the epidemiological feature of the coffee rust disease, most of the coffee rust experts reached the consensus that "the key to successful coffee rust control is in applying fungicides preventively." (Avelino et al. 2015). Therefore, the difference between the reactive nature of organic pesticides and the preventive nature of synthetic pesticides is a key predictor for the intensity of the disease dispersal.

**Coffee Rust** The plant disease coffee leaf rust, formally known as *Hemileia Vastatrix*, is a pathogen affecting only coffee leaves. If infected, coffee plants, after 30 days of incubation period, start showing yellow spots on their leaves and defoliate, and, if not treated, they eventually die (Avelino, Willocquet, and Savary 2004). Given that coffee rust is a long-distance-dispersal disease, the airborne fungal spores are easily spread by wind and rain from plant to plant and from plantation to plantation if they happen to be in proximity with each other.

### 3 Data

I combine several datasets from various sources to construct the final dataset, which comprises 142 Guatemalan municipalities presented in Figure 13 in the appendix. If a municipality has more than 5% of agricultural land dedicated to coffee, it qualifies to be part of the sample. The different datasets are merged by administration code and geographical coordinates. To study the mechanisms, I combine numerous datasets at the census block level and farm level, for a total of 350 units of observation. Figure 1 below summarizes the main datasets used in this study and their respective temporal coverage. The summary statistics for the most important variables are presented in Table 1.

**Emigration** All the outcome variables are retrieved from the 2018 National Census<sup>10</sup>. This census provides information on the number of emigrants per household in the previous 15 years and their main characteristics, such as gender and age, for the entire territory of Guatemala. It is worth noticing that, as this data comprises of all households in Guatemalan territory as of 2018, if an entire household emigrates abroad before 2018, it disappears from my sample. To the extent that the relationship under scrutiny in

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<sup>10</sup>XII Censo Nacional de Población y VII de Vivienda (INE) <https://www.censopoblacion.gt>

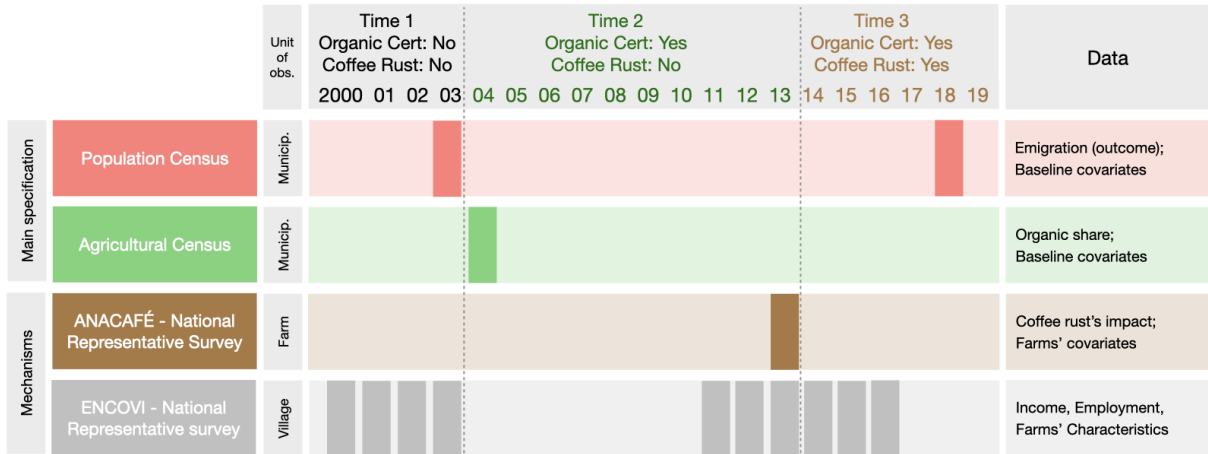


Figure 1: Description of the data

this study is monotonic, this should generate only an attenuation bias. From this data I compute the major outcome variable of this study, namely the emigration rate, whose geographical variation is presented in Figure 15 in appendix.

**Endogenous Variables** The independent endogenous variable, i.e. the share of organic coffee farmers within a municipality, is extrapolated from the National Agricultural Census in 2003<sup>11</sup>, for a total of 330 units of observation. Specifically, the organic coffee farmer share is computed as the share of coffee farmers that reported to not use chemical pesticides in their farm in the agricultural census. The cross-sectional variation is presented in Figure 14 in appendix.

**Instrumental Variable** To create the instrumental variable, I use two different datasets: the network of roads in Guatemala and the list of cooperatives that received organic certification before 2006. The former dataset, provided by the National Geographic Institute of Guatemala<sup>12</sup>, allows me to observe the location, the extent and the status of each road in the country, i.e. whether it is paved and its number of carriageways. With this data I can compute the travel distance between any two points in the country, such as the travel distance between the centroid of each municipality and the closest organic cooperatives or the major exporting harbors. The latter dataset is a result of a web-scraping exercise and data collection in the field. I match three different data sources: the list of clients

<sup>11</sup>Instituto Nacional de Estadística. IV Censo Nacional Agropecuario. (2005) <https://www.ine.gob.gt/ine/censo-agropecuario/>

<sup>12</sup>Instituto Geográfico Nacional Ing. Alfredo Obiols Gómez (IGN) <https://www.segeplan.gob.gt>



of the major certifier in the country, the list of active cooperatives in the country, and the certified companies listed by the country-specific certification bodies, such as USDA Organic or IFOAM Organics Europe<sup>13</sup>. The outcome of this exercise is a list of cooperatives in the coffee sector, with information on whether and when they obtained an organic certification.

Table 1: Summary Statistics

	mean	sd
<u>A. Outcome Variables</u>		
Emigration Rate	0.068	0.083
Share of HH with Emigrants	0.012	0.014
Number of Emigrants	357.354	500.887
Age of Emigrants	25.772	2.863
Gender of Emigrants	0.752	0.112
<u>B. Endogenous Variables</u>		
Share of Organic Coffee Farms	0.353	0.270
<u>C. Instrumental Variables</u>		
Average Distance to First Organic Cooperatives	19.963	15.115
<u>C. Control Variables</u>		
Altitude	1294.578	623.786
Distance to the Capital	9.753	9.406
Total Area	18765.278	25984.620
Market Access	11.012	9.624
Number of Coffee Farms	963.908	1588.725
Coffee Cultivated Area	2479.577	2815.911
Share of Agricultural Land Dedicated to Coffee	0.391	0.305
Literacy Rate	0.678	0.123
Age	22.889	1.591
Share of Indigenous Population	0.427	0.403
Share of Population Economically Active	0.294	0.055
Number of Housholds	5675.289	5413.011
Household's size	5.244	0.508
Gender	0.495	0.009

*Notes:* The unit of observation is a municipality. All variables are computed as average within a municipality. The emigration rate is referred to the population 15-65 years old. The distance variables are measured in kilometers. The altitude is measured in meters. Areas are measured in hectares. Market access is a score that varies between 0 and 170. Gender variables are computed as the share of male individuals (male=1). There are 142 observations for each variable.

<sup>13</sup>mayacert.com, ceres-cert.com, inacop.gob.gt. For each website I retrieve the archived version using the Wayback Machine service at archive.org, an open-source digital archive of the World Wide Web

**Other datasets** To select the sample, i.e. the municipalities where coffee is the major cultivated crop, I compute the proportion of agricultural land dedicated to coffee within a municipality. I retrieve this information using a map produced by GIMBOT<sup>14</sup>, which uses *RapidEye*, a high-spectral resolution satellite dataset, to classify the use of land in Guatemala from 2001 to 2016. The baseline control variables are extracted from the 2002 National Census<sup>15</sup> and the National Agricultural Census in 2003. All the meteorological control variables at the municipality and farm level are extracted from the CRU TS v4.05, a high-resolution gridded dataset provided by the Climate Research Unit at the University of East Anglia (Harris et al. 2020), and matched to the centroid of each municipality.

All the data used to understand how Guatemalan emigrants form the decision to migrate and which destination country they choose are provided by the UN agency International Organization for Migration (OIM). I use two sources: the *Encuesta sobre Migración Internacional de Personas Guatemaltecas y Remesas 2016*, a national representative survey which gathers data on the identity of the emigrants, their relationship with the household in Guatemala and the reasons to emigrate; and the Workbook: UN Migrant Stock by Origin and Destination in 2017.

**Mechanisms** The intensity of CR in the coffee plantations, is based on an on-site national representative survey run by ANACAFÉ, the national coffee association in Guatemala, among 1328 coffee farms in the 2012/13 harvest season<sup>16</sup>. I can observe the intensity of CR in the plantation and the estimated impact on production. As ANACAFÉ does not represent the entire spectrum of coffee farmers in the country, one might be concerned about selection and geographical representation. For this purpose, I use machine learning techniques, specifically random forest, and the high-spectral resolution satellite dataset Landsat 7<sup>17</sup> to predict the intensity of CR in all coffee cultivated areas. Figure 16 in appendix shows the result of this exercise. I then collapse the score obtained from this exercise at the municipality level.

Finally, the information related to income and employment is extracted from the Living Standards Measurement Survey (*Encovi*) developed by the Guatemalan Statistics

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<sup>14</sup>*Mapa de bosques y uso de la tierra 2012 y Mapa de cambios en uso de la tierra 2001-2010*. Grupo Interinstitucional de Monitoreo de Bosques y Uso de la Tierra. (2014)

<sup>15</sup>Censo Nacional de Población 2002 (INE) <https://www.ine.gob.gt/ine/censo-2002/>

<sup>16</sup>Asociación Nacional del Café <https://www.anacafe.org/>

<sup>17</sup><https://earth.esa.int/eogateway/missions/landsat-7>

Bureau (INE). Encovi is a comprehensive, cross-sectional household survey that collects information on a wide range of aspects covering the main demographic, social, and economic characteristics of the population. The sample consists of approximately 13,500 households and is representative at the national, urban, rural, regional and state levels.

## 4 Identification Strategy

**OLS Specification** The simplest way of looking at the effect of organic farming on emigration is to run the following OLS regression

$$Y_m = \alpha_2 + \beta Organic\_Share_m + \mathbf{X}'_m \mathbf{\Gamma} + \varepsilon_m, \quad (1)$$

where  $Y_m$  denotes the emigration rate, or any outcome related to emigration in municipality  $m$  after 2013.  $Organic\_Share_m$  captures the share of coffee farmers that are organic in municipality  $m$  in 2006.  $\mathbf{X}'_m$  is a vector of covariates of interest at the municipal level, such as the emigration rate before 2012, the size of coffee cultivated areas, the access to markets.  $\varepsilon_{i,m}$  is an idiosyncratic error term. The parameter of interest  $\beta$  captures the percentage-points (p.p.) increase in emigration rate associated with an increase of 1 standard deviation (SD) in the share of organic coffee farms.

**OLS Results** In table 2, I show the OLS results based on equation 1. A 1 SD increase in the share of organic farms within a municipality is correlated with a 1.8 p.p. increase in emigration rate. This result cannot be interpreted causally as it is prone to many sources of endogeneity. For instance, coffee producers can opt in or out of organic farming depending on their income level, the level of market access, or their socio economic characteristics. By controlling for most of these baseline characteristics, I show in column 6 that the positive correlation actually disappears.

Nevertheless, even after including many controls, the OLS estimates might still be prone to an omitted variable bias. For instance, producers might self-select into organic farming based on expectations of future earnings, or different levels of risk aversion. Furthermore, the OLS estimates are not so interesting from a policy perspective as they also include the effects of organic farming for those farmers that would have joined organic

Table 2: OLS Estimation of Main Effects

Dependent Variable:	Emigration Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Share (SD)	0.018*** (0.007)	0.013* (0.007)	0.006* (0.004)	0.005 (0.004)	0.005 (0.004)	0.003 (0.005)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.05	0.19	0.82	0.84	0.85	0.85
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The emigration rate is referred to the population 15-65 years old. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

farming anyway (always takers) and those that would have never joined organic farming (never takers), thus a difficult target group by any intervention.

**Instrumental-Variable Strategy** To overcome the issues raised above, I use an instrument for the share of organic farms within a municipality. The instrumental variable can be defined as the average distance from the centroid of the coffee farms in each municipality  $m$  to the closest  $K$  organic certified cooperatives, indexed by  $j$ , part of the first wave of organic certifications, i.e. pre-2006:

$$IV_m = \frac{\sum_{j=1}^K distance_{mj}}{K}.$$

Intuitively, this instrument captures how much each municipality was exposed to the first wave of organic certifications: the higher the value of the instrument, the lower the exposure intensity. Throughout this paper, I make the decision of  $K=3$ . As this is totally an arbitrary decision based on both the total number of cooperatives and organic certified cooperatives per municipality, I show later in the paper and in appendix that my results are robust allowing  $K > 3$  or  $K < 3$ .

To compute the distance I use two methods: the straight-line distance in kilometers

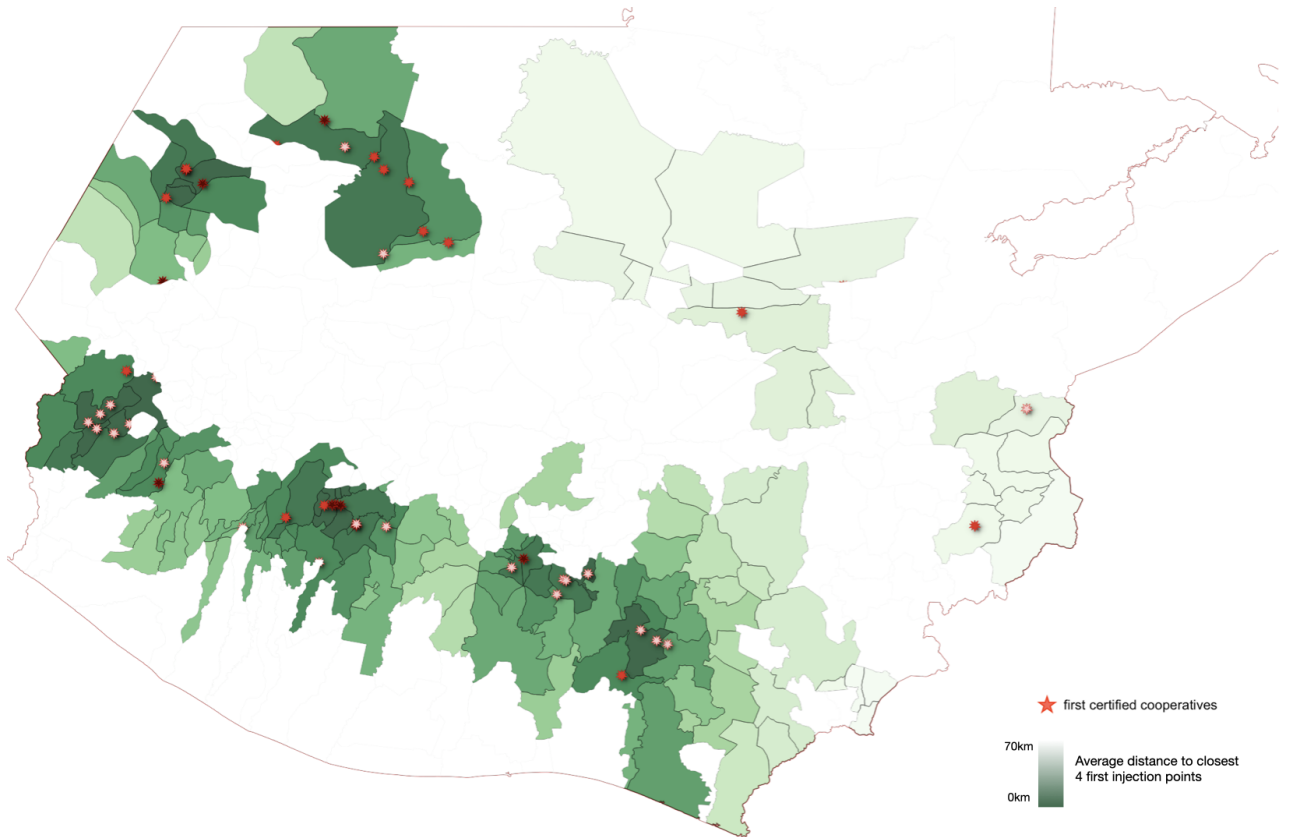


Figure 2: Construction of the Instrument

and the driving distance, i.e. a measure of distance that captures not only the distance aspect of proximity but also the costs that terrain imposes on travel time (Rogall 2021; Heldring 2021)<sup>18</sup>. The latter is the preferred one and is presented in Figure 2, which shows the cross-sectional variation of the instrument across municipalities.

My identification strategy relies on three key assumptions. First, municipalities closer to the first organic certified cooperatives experienced higher shares of organic coffee farms (first stage). Second, the distance of each municipality to the first organic cooperatives is as good as random (exogeneity). Third, conditional on the control variables, distance to the first organic cooperatives does not have a direct effect on emigration other than through organic farming (exclusion restriction).

**First Stage** The decision for a farmer to become organic implies various complex assessments, as it involves a cost-benefit analysis, an estimation of the long-term trends in the market, as well as personal preferences. Moreover, as the majority of farmers are also members of cooperatives, the decision is often not taken in isolation, but influenced

<sup>18</sup>Another possibility is the Human Mobility Index (Özak 2012)

by the choices and experiences of neighboring farmers. Anecdotal evidence shows indeed that the diffusion of organic certifications happens by a big extent by word of mouth.

To confirm this conjecture, I went into the field in December 2021 to collect data and run focus groups with coffee producers. The results show that the majority of interviewed organic certified farmers considered receiving an organic certification only after speaking with another organic certified producer. This suggests that, keeping all other variables constant, being closer to an organic certified farmer or cooperative makes a producer more likely to transition to organic farming. This is in line with the salience theory of choices under risk.

This hypothesis can also be tested in the data with the following equation

$$Organic\_Share_m = \alpha_1 + \gamma IV_m + \mathbf{X}'_m \boldsymbol{\Gamma} + u_m, \quad (2)$$

where  $IV_m$  is the instrumental variable that captures the exposure of farmers to the first organic certified cooperatives, and all other variables are as described above. The parameter of interest  $\gamma$  shows the correlation between the instrument and the share of organic farms within a municipality. In table 3 I present the results for the first stage regression. The instrument seems to have predictive power on the endogenous regressor: a 1 SD increase in the value of the instrument leads to a 0.25 SD decrease in the share of organic farms within a municipality. This result is robust to the inclusion of several farm level and municipality level covariates, and geographic characteristics. The F-statistic is well above 10, suggesting that, according to the rule of thumb (Stock and Yogo 2002), the instrument is not weak.

**Exogeneity** The intuition behind the exogeneity of the instrument is the presence of only one local certifier in the country, which provides still nowadays certifications to 75% of all organic certified producers. Based on an in-person interview with the CEO of this certification company, it appears that, at its very beginning, the business model of this company was to reach out directly to cooperatives and producers, whom the CEO was in personal contact with. This crucial observation allows me to presume that the first cooperatives to receive organic certifications were not strategically targeted neither to reduce emigration nor to address the problem of coffee rust in the regions. Therefore,

Table 3: First Stage Results

Dependent Var:	Organic Share (SD)					
	(1)	(2)	(3)	(4)	(5)	(6)
IV (SD)	-0.418*** (0.077)	-0.373*** (0.086)	-0.388*** (0.085)	-0.273*** (0.073)	-0.284*** (0.073)	-0.252*** (0.078)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
R-squared	0.18	0.31	0.36	0.60	0.63	0.64
F-statistic	29.73	20.50	15.43	20.04	17.08	15.99
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All variables are measured in SD. The organic share is the proportion of organic coffee farmers out of all coffee farmers. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the emigration rate over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

I proceed by testing that the instrument is indeed as good as random, and I show the results in Table 4.

First, the instrument seems to not capture different emigration rate pre-2013. Second, as the headquarter of the only local certifier is based in the capital Guatemala City, I test whether the instrument is capturing the variation in travel distance to the capital, i.e. whether the areas closer to the first organic certified cooperatives are more connected to the capital. The instrument seems to pass this test as well.

The instrument seems to pass further tests. For instance, I check whether municipalities closer to the first organic certified cooperatives happen to have a higher population, higher education levels, and higher income per capita. I check that the instrument is not capturing variation in the total number of cooperatives within the municipalities.

I then test whether the source of variation in the instrument is the same as the market access, i.e. municipalities closer to the first organic certified cooperatives happened to be also more connected to markets. In order to test this hypothesis, I use the same formula employed for the computation of the instrumental variable, while replacing the focal points with the two major exporting harbors in Guatemala: one facing the Pacific

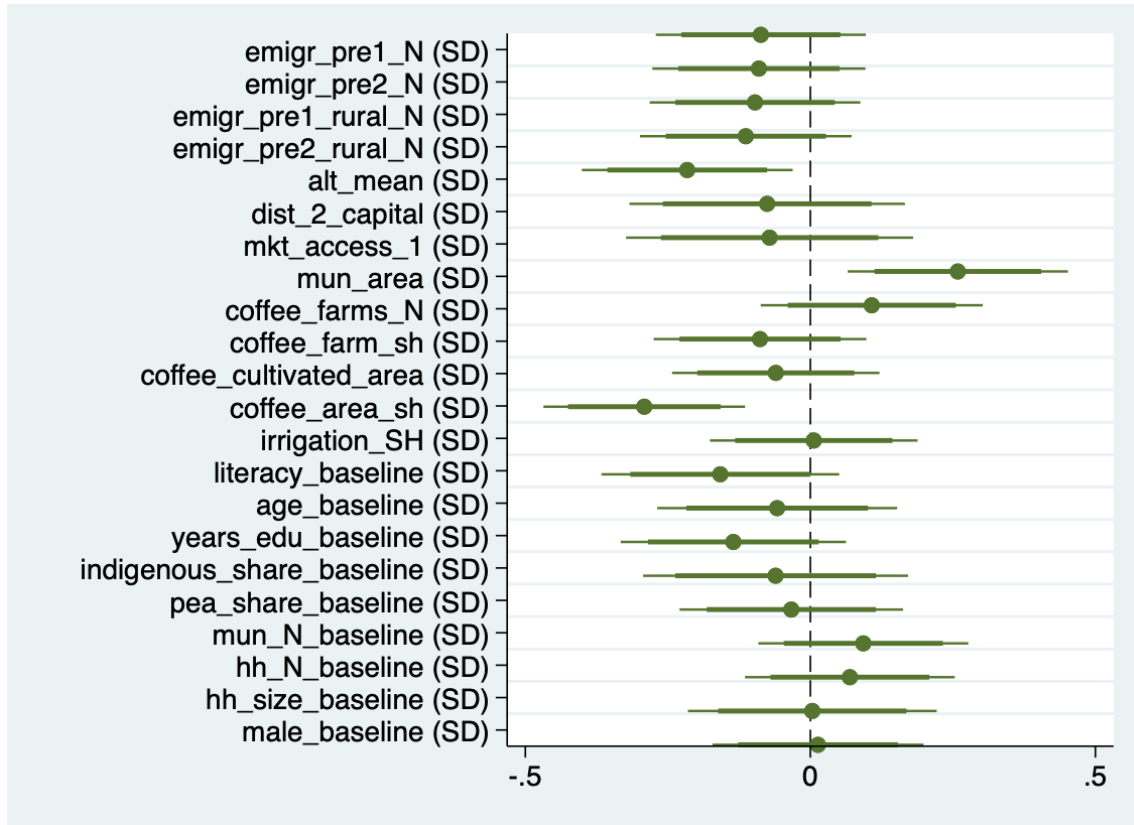


Figure 3: Balance test of the instrument

ocean and one facing the Atlantic ocean. Figure 17 in appendix shows this exercise on a map.

Lastly, as anecdotal evidence suggests that coffee rust was not prevalent in Guatemala before 2012, it is reasonable to assume that the instrument is not capturing pre-trends in the spread of coffee rust. Consequently, the only variables that seem to be correlated with the instrument are the average altitude, the municipality area and share of land dedicated to coffee. These correlations are not surprising as by construction the instrument captures any variation in distance or scale effects. Consequently, I can easily control for all these variables in all specifications throughout this paper.

**Exclusion Restriction** The identification strategy relies on the counterfactual assumption that, in absence of the option of becoming an organic coffee farmer, being closer to an organic certified cooperative does not have a direct effect on the municipality’s emigration rate. I provide some suggestive evidence that this is in deed the case by performing two placebo tests. The results are presented and discussed in more details the robustness section, so I limit myself to explaining the basic intuition in this section.



First, I check the main results do not replicate once I select as sample not-coffee municipalities, i.e. municipalities with less than 10% of agricultural land dedicated to coffee. Intuitively, if some of these municipalities happen to be close to FOCC, but have little or no coffee cultivated land, I should not observe any effect on emigration. Second, if we run the 2SLS specification on emigration rates before 2012 and we get not statistically significant effect, we have suggestive evidence that the effects on emigration show up only when the coffee rust appears in the region, implying that the mechanism through which certifications affect the emigration decision is the organic farming and the spread of plant diseases.

**IV Specification** The main empirical strategy relies on the following Two-Stage least squares (2SLS) regression analysis:

$$Y_m = \alpha_2 + \beta_{IV} \widehat{Organic\_Share}_m + \mathbf{X}'_m \boldsymbol{\Gamma} + \varepsilon_m, \quad (3)$$

$$Organic\_Share_m = \alpha_1 + \gamma IV_m + \mathbf{X}'_m \boldsymbol{\Gamma} + u_m, \quad (4)$$

where  $Y_m$  denotes the emigration rate after 2013 in municipality  $m$ , or any other outcome variable related to emigration.  $Organic\_Share_m$  captures the share of coffee farmers that are organic in municipality  $m$  in 2005.  $\mathbf{X}'_m$  is a vector of covariates of interest at the municipal level, such as the emigration rate before 2012, the size of coffee cultivated areas, the access to markets.  $\varepsilon_{i,m}$  is a robust error term.

$IV_m$  is the instrumental variable described in the previous section and captures the average travel distance to the first organic certified cooperatives, which we can simplify with the acronym FOCC. The parameter of interest  $\beta_{IV}$  captures the ATT, i.e. the causal effect of organic farming on emigration for those producers induced to join organic farming by the spread of organic certifications. To consider  $IV_m$  a valid instrument, I need to assume, first, that the impact of the instrument on emigration is exclusively mediated by the decrease in the use of chemical pesticides, i.e.  $cov(IV_m, \varepsilon_m) = 0$ . Second, I need to assume that the first organic certifications were not given strategically to coffee regions relatively more affected by coffee rust before 2012 and with higher emigration rates, i.e.  $cov(IV_m, u_m) = 0$ . Both these assumption have been discussed and addressed above.

## 5 Results

**Emigration Rate** In table 4 I present the results of the instrumental variable strategy presented in equations 3 and 4. I find that a 1 SD increase in the share of organic farms in a given municipality leads to 3.2 p.p. increase in the emigration rate in the same municipality, which corresponds to a almost 50% increase in emigration rate. The magnitude and significance of the estimate seem to survive the inclusion of several control variables. Compared to the OLS estimates presented above, the instrumental-variable coefficients suggest that organic farming had indeed an impact on emigration rate. Similar results are found if we select as outcome variable the share of households that has at least one member who emigrated after 2013. the results are presented in Table 11 in appendix.

Table 4: 2SLS Estimation of Main Effect

Dependent Variable:	Emigration Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Share (SD)	0.027* (0.016)	0.070*** (0.025)	0.037*** (0.012)	0.037** (0.016)	0.033** (0.015)	0.032** (0.016)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.04	0.19	0.72	0.78	0.80	0.81
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The emigration rate is referred to the population 15-65 years old. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

To better understand at what point in time the effects appear, in figure 4 I use the same 2SLS strategy described above, with the only difference that the outcome variable is the number of emigrants per municipality per year. I use the predicted organic share from the first stage to split the sample between municipalities with above the median and below the median organic share. The figure shows that in the 10 years before the coffee rust appeared, i.e. in 2012/13, emigration rates are almost the same. However,

after 2013 the areas with high organic share experience twice as many emigrants, and the trend seems to be larger year after year.

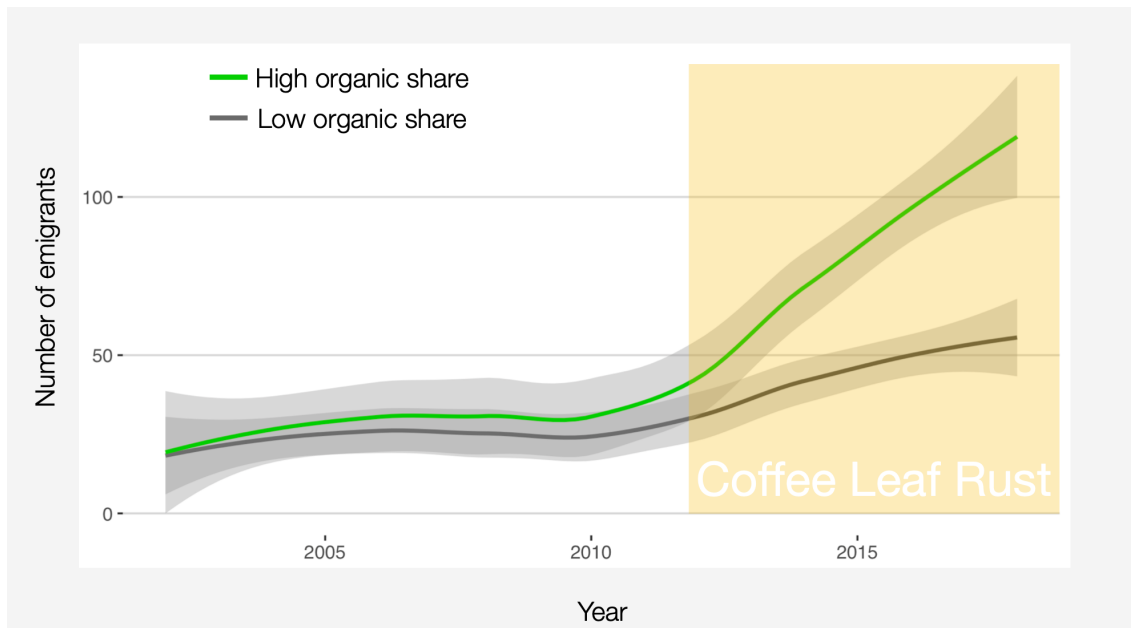


Figure 4: Time Trend of Emigration

It is worth noting that I measure the local average treatment effect (LATE) induced by changes in organic farming due to the instrument. Farmers induced to start organic agriculture because of organic certifications might be more responsive than the average organic farmer, resulting in a high local average treatment effect. However, part of this difference might be attenuated by the composition of the emigrant population, because the effect on emigration comprises the effect on coffee farmers and on the hired labor during harvest season. For this reason I proceed in the next paragraph to investigate the identity of emigrants.

**Identity of Emigrants** In figure 5 I show the age distribution of the emigrant population, as before, by splitting the sample between municipalities with above the median and below the median predicted organic share. I show the distribution for the period before and after 2013, i.e. before and after the coffee rust arrived in Guatemala. As expected, regardless of the share of organic farms within a municipality, the age distribution seems to be the same pre 2013 and there is an overall increase in number of emigrants post 2013. However, with the arrival of the coffee rust, it appears that the relatively younger population in areas with high organic share emigrates the most, especially around 20

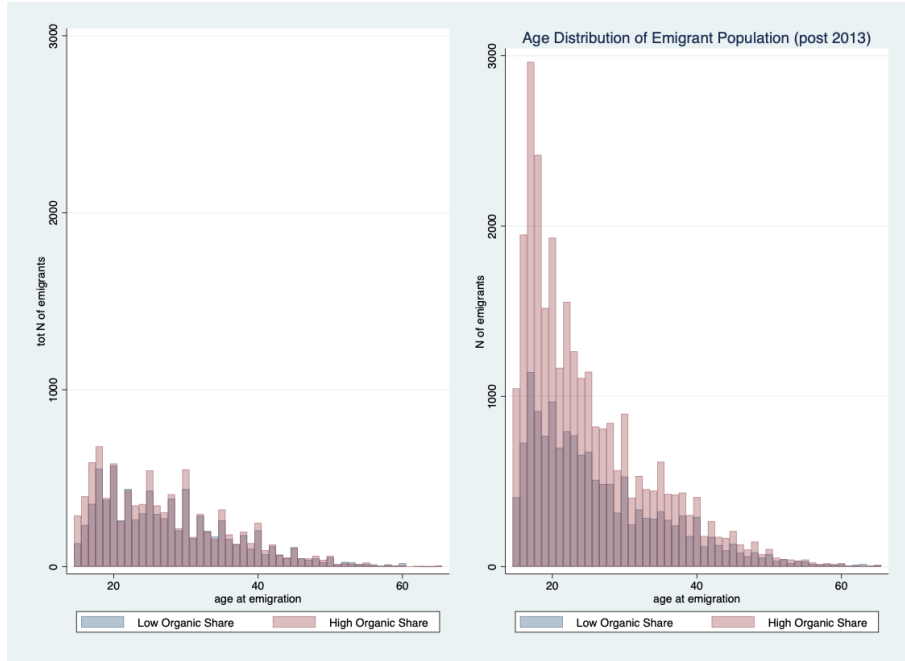


Figure 5: Age of Emigration by Organic Share (pre/post)

years old. Considering that these results are at the aggregate level, it is unclear whether households of coffee farmers or of hired labour during the harvest seasons are the ones responding the most. Further investigation on this margin is still ongoing.

## 6 Robustness Checks

**Variation of IV and Sample** There are two major arbitrary decisions that I made throughout the paper to select the sample and to define the instrument. These are, respectively, the share of agricultural land dedicated to coffee that defines whether a municipality is part of my sample or not and the number of cooperatives used to compute the instrument.

First, as far as the sample criterion is concerned, I assumed that, if a municipality has less than 5% of agricultural land dedicated to coffee, it does not qualify to be part of the sample. I show in figure 6 that by slightly increasing and decreasing this threshold, the magnitude of the effect does not vary substantially. Second, in the same figure I show that, by constructing the instrument using more or less than  $K = 3$  closest cooperatives, the results do not vary to a large extent. However, it appears that setting  $K = 1$  or  $K = 2$  drops the magnitude of the main effect close to 0. This result can be explained by the

low predictive power of the instrument on the endogenous variable *Organic Share*, i.e. we run into a weak instrument issue.

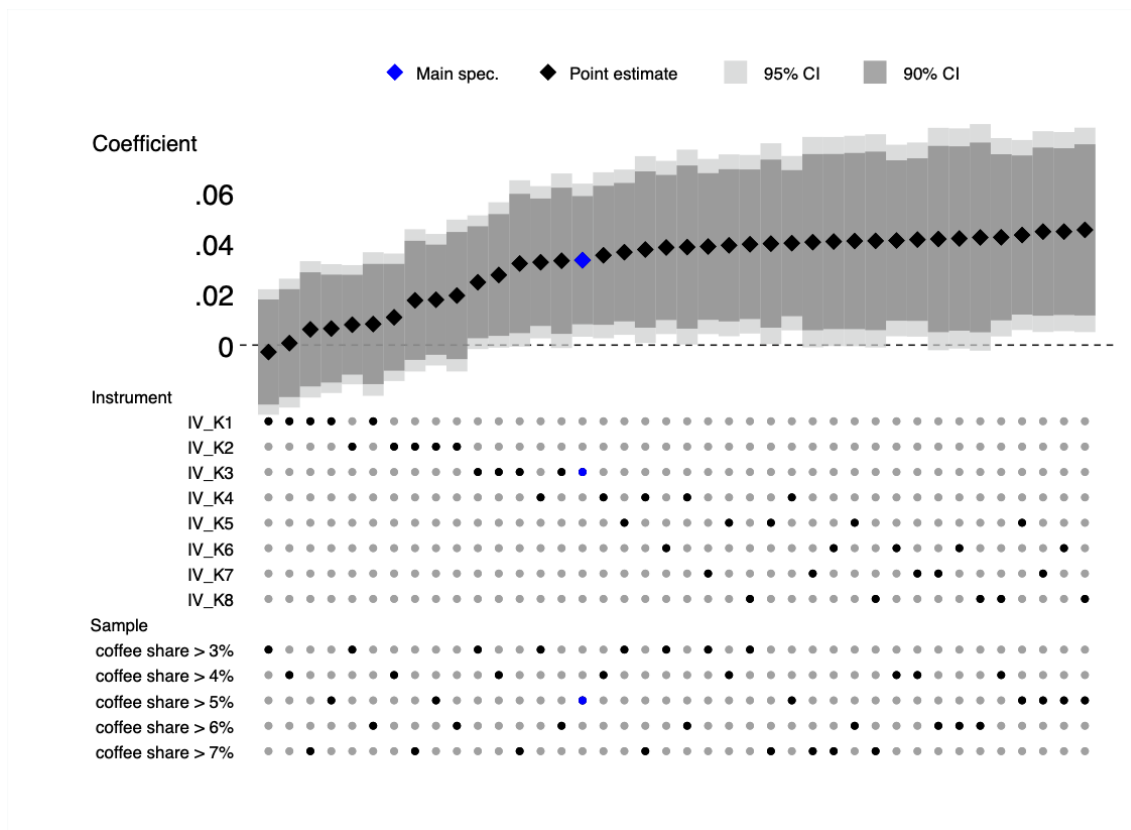


Figure 6: 2SLS Estimates by Different Sample and Instrument Thresholds

**Placebo Tests** I provide three types of placebo test. In the first one, presented in Figure 12 in appendix, I replicate the 2SLS analysis selecting only the urban areas within the sample of coffee municipalities. Intuitively, I should not observe any effect as coffee rust should not have affected the urban population. the magnitude of the effect decreases and none of the main estimates is statistically significant.

In the second one, presented in Figure 13 in appendix, I replicate the 2SLS analysis 5 years before the arrival of the CR, i.e. between 2007 and 2012. Once again, I should not observe any effect as the major mechanism of the increased spread of the disease in organic farmed areas is not present. None of the main estimates is indeed significant.

In the third one, presented in Figure 14 in appendix, I perform a similar exercise as before, by selecting as my sample only those municipalities where coffee is not produced. None of the main estimates is indeed significant.

## 7 Mechanisms

This section explores the major mechanism: the impact of organic farming on the spread of the major plant disease affecting coffee: the coffee leaf rust (CR). Further study on the economic impact is still ongoing, so the reader should interpret this as preliminary evidence. By changing the outcome variable in equation 3, we can test whether organic farming, induced by organic certifications, led to an increase in the spread of the CR disease. The results in Table 5 show that a 1 SD increase in the share of organic farms in a given municipality led to 40% increase in the infection rate from CR.

Table 5: 2SLS Estimation of Effect on Coffee Rust

Dependent Variable:	Coffee Rust					
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Share (SD)	0.20*** (0.08)	0.18** (0.08)	0.17** (0.08)	0.22*** (0.07)	0.22** (0.09)	0.22** (0.10)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.45	0.45	0.45	0.45	0.45	0.45
R-squared	0.04	0.19	0.72	0.78	0.80	0.81
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The coffee rust score takes value between 0 and 1 and captures the intensity of the spread of coffee rust within the municipality. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

	Unit of obs.	Time 1	Time 2	Time 3	Data	
		Organic Cert: No Coffee Rust: No	Organic Cert: Yes Coffee Rust: No	Organic Cert: Yes Coffee Rust: Yes		
		2000 01 02 03	04 05 06 07 08 09 10 11 12 13	14 15 16 17 18 19		
Main specification	Population Census	Municip.	[Timeline bars for Population Census]			Emigration (outcome); Baseline covariates
	Agricultural Census	Municip.	[Timeline bars for Agricultural Census]			Organic share; Baseline covariates
Mechanisms	ANACAFÉ - National Representative Survey	Farm	[Timeline bars for ANACAFÉ]			Coffee rust's impact; Farms' covariates
	ENCOVI - National Representative survey	Village	[Timeline bars for ENCOVI]			Income, Employment, Farms' Characteristics

Figure 7: Description of the data

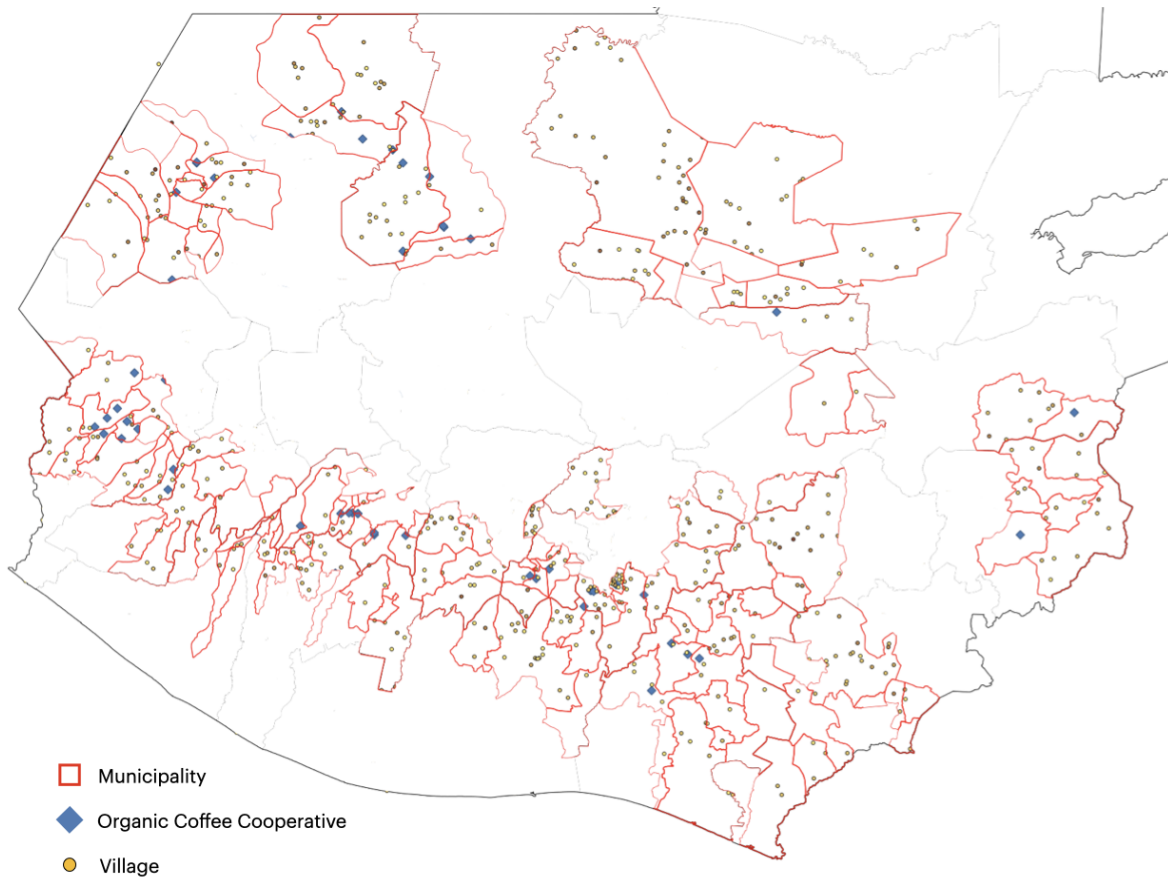


Figure 8: Villages part of ENCOVI National representative survey

**DiD Specification** The empirical strategy relies on the following Difference in Difference (DiD) regression analysis:

$$\log(Y_{i,m,t}) = \alpha + \beta_t Dist_i * Time_t + \gamma Dist_i + \delta_t Time_t + \lambda_m + \varepsilon_i, \quad t = 1, 2, 3 \quad (5)$$

where  $Y_{i,m,t}$  denotes the outcome variable of village  $i$  in municipality  $m$  in period  $t$ .  $Dist_i$  is the distance in Km from village  $i$  to the closest organic certified coffee cooperative.  $Time_t$  is dummy equal to 1 for period= $t$ .  $\varepsilon_{i,t}$  is an idiosyncratic error term, corrected for spatial correlation within a radius of 100km (Conley 1999). The parameters of interest  $\beta_2$  and  $\beta_3$  capture respectively the percentage increase in  $Y$  induced by an 1Km increase in the distance of village  $i$  to the closest organic certified coffee cooperative in time 2 and in time 3.

$$\log(Y_{i,m,t}) = \alpha + \sum_{t=2000}^{2016} \beta_t Dist_i * Year_t + \gamma Dist_i + \sum_{t=2000}^{2016} \delta_t Year_t + \lambda_m + \varepsilon_i, \quad (6)$$

$$t = 2000, 2001, \dots, 2016. \quad (7)$$

where  $Y_{i,m,t}$  denotes the outcome variable of village  $i$  in municipality  $m$  in period  $t$ .  $Dist_i$  is the distance in Km from village  $i$  to the closest organic certified coffee cooperative.  $Year_t$  is dummy equal to 1 for year= $t$ .  $\varepsilon_{i,t}$  is an idiosyncratic error term, corrected for spatial correlation within a radius of 100km (Conley 1999). The parameters of interest  $\beta_t$  capture the percentage increase in  $Y$  induced by an 1Km increase in the distance of village  $i$  to the closest organic certified coffee cooperative in year  $t$ .



Table 6: DD Estimation of Effect on Farms

	(1) Number of Farms	(2) Number of Employees	(3) Profit
year=2002 X Dist	-0.027 (0.020)	-0.007 (0.012)	-0.016 (0.012)
year=2003 X Dist	-0.008 (0.018)	-0.013 (0.011)	-0.016 (0.016)
year=2011 X Dist	0.061 (0.037)	-0.022 (0.020)	-0.024 (0.015)
year=2012 X Dist	0.004 (0.026)	-0.022 (0.017)	-0.008 (0.013)
year=2013 X Dist	-0.004 (0.047)	-0.016 (0.025)	-0.009 (0.013)
year=2014 X Dist	0.093** (0.043)	-0.039 (0.052)	-0.020 (0.016)
year=2015 X Dist	0.042** (0.021)	-0.033* (0.019)	-0.031** (0.013)
year=2016 X Dist	0.067*** (0.024)	-0.009 (0.014)	-0.029** (0.012)
R-squared	0.03	0.07	0.03
N. of obs	926	221	596

*Notes* The unit of observation is the village. All outcome variables are measured in log. Standard errors are corrected for spatial correlation within a radius of 100km (Conley 1999). Statistical significance levels: \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

Table 7: DD Estimation of Employment Effect (Extensive Margin)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Inactive	Unemployed	Employed	Hours worked	Employed (in Agr.)	Employee (in Agr.)	Day Labourer (in Agr.)	Employer (in Agr.)	Self-Employed (in Agr.)
year=2001 X Dist	-0.002 (0.002)	0.006 (0.007)	0.001 (0.002)	-0.003** (0.002)	-0.003 (0.005)	0.005 (0.010)	-0.017** (0.008)	0.002 (0.007)	0.008 (0.008)
year=2002 X Dist	-0.000 (0.002)	0.010 (0.007)	0.000 (0.001)	-0.004*** (0.001)	-0.002 (0.007)	0.001 (0.010)	-0.028*** (0.007)	0.005 (0.007)	0.010 (0.007)
year=2003 X Dist	-0.002 (0.002)	0.014* (0.008)	0.002 (0.002)	-0.003** (0.001)	0.007 (0.006)	0.001 (0.010)	-0.006 (0.007)	-0.008 (0.008)	0.006 (0.007)
year=2011 X Dist	-0.001 (0.002)	0.007 (0.007)	0.000 (0.002)		0.013 (0.008)	-0.002 (0.012)	-0.002 (0.008)	-0.002 (0.009)	0.020** (0.010)
year=2012 X Dist	-0.003 (0.002)	-0.005 (0.007)	0.002 (0.002)	-0.002 (0.001)	-0.003 (0.008)	0.023** (0.011)	-0.004 (0.009)	-0.010 (0.011)	0.008 (0.009)
year=2013 X Dist	-0.003 (0.002)	-0.008 (0.007)	0.002 (0.002)	-0.004*** (0.001)	-0.007 (0.008)	-0.010 (0.011)	0.025*** (0.007)	0.004 (0.008)	0.007 (0.011)
year=2014 X Dist	-0.004* (0.002)	-0.001 (0.007)	0.002 (0.001)	-0.003* (0.001)	0.021*** (0.007)	0.003 (0.019)	0.017* (0.009)	-0.030 (0.024)	0.027*** (0.008)
year=2015 X Dist	-0.005** (0.002)	0.008 (0.006)	0.003* (0.002)	-0.005*** (0.001)	0.009 (0.007)	0.000 (0.009)	-0.002 (0.007)	0.017 (0.014)	0.021** (0.008)
year=2016 X Dist	-0.007*** (0.002)	0.005 (0.006)	0.004*** (0.001)	-0.004*** (0.002)	0.013* (0.007)	0.003 (0.010)	0.018** (0.007)	-0.009 (0.008)	0.019** (0.008)
R-squared	0.01	0.04	0.01	0.01	0.02	0.01	0.07	0.05	0.02
N. of obs	1159	390	1161	926	1004	383	713	196	831

Notes The unit of observation is the individual. All regressions include fixed effects for each year and each UPM (Primary Sample Unit), which corresponds to a populated places. Standard errors are clustered at the UPM level. Statistical significance levels: \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

Table 8: DD Estimation of Income Effect

	(1)	(2)	(3)	(4)	(5)
	Total Income	Labor Income	Wage Income (in Agr.)	Non-wage Income (in Agr.)	Remitt.
period=2001 × IV	-0.000 (0.006)	0.001 (0.006)	-0.010 (0.010)	0.036** (0.017)	-0.005 (0.019)
period=2002 × IV	0.001 (0.004)	0.000 (0.004)	-0.012* (0.007)	0.037*** (0.010)	0.028* (0.015)
period=2003 × IV	0.008*** (0.003)	0.002 (0.004)	-0.002 (0.009)	0.022 (0.015)	0.028** (0.012)
period=2011 × IV	-0.007 (0.006)	-0.006 (0.006)	-0.002 (0.010)	0.022 (0.019)	-0.012 (0.020)
period=2012 × IV	0.004 (0.007)	0.003 (0.008)	0.009 (0.008)	0.037** (0.015)	-0.002 (0.012)
period=2013 × IV	0.002 (0.005)	0.001 (0.006)	-0.017** (0.008)	0.038** (0.017)	-0.001 (0.011)
period=2014 × IV	0.001 (0.005)	0.002 (0.005)	0.025** (0.011)	0.039** (0.016)	0.024 (0.019)
period=2015 × IV	-0.003 (0.004)	-0.002 (0.005)	-0.003 (0.008)	0.014 (0.014)	-0.001 (0.012)
period=2016 × IV	0.002 (0.004)	0.001 (0.005)	0.014 (0.010)	0.017 (0.013)	0.024** (0.010)
Mean	7.97	7.76	5.82	5.24	4.73
R-squared	0.44	0.44	0.31	0.34	0.35
N. of obs	1145	1145	833	845	610

*Notes* The unit of observation is the household. All outcome variables are measured in log. Standard errors are clustered at the municipality level. Statistical significance levels: \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

Table 9: DD Estimation of Effect on Farms

	(1) Number of Farms	(2) Number of Employees	(3) Profit
year=2002 X Treat	1.089* (0.641)	-0.024 (0.356)	0.484 (0.393)
year=2003 X Treat	0.329 (0.612)	0.339 (0.393)	1.472*** (0.524)
year=2011 X Treat	-1.284 (0.932)	1.516** (0.664)	1.135** (0.459)
year=2012 X Treat	-0.341 (0.918)	0.158 (0.554)	0.784* (0.447)
year=2013 X Treat	-0.267 (1.509)	-0.545 (0.865)	0.912** (0.429)
year=2014 X Treat	-1.964 (1.239)	0.667 (0.580)	0.801* (0.424)
year=2015 X Treat	-0.775 (0.652)	0.253 (0.732)	1.254*** (0.410)
year=2016 X Treat	-1.123 (0.711)	0.055 (0.499)	1.100*** (0.394)
R-squared	0.02	0.07	0.04
N. of obs	926	221	596

*Notes* The unit of observation is the village. All outcome variables are measured in log. Standard errors are corrected for spatial correlation within a radius of 100km (Conley 1999). Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 10: DD Estimation of Employment Effect (Extensive Margin)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inactive	Unemployed	Employed	Employed (in Agr.)	Employee (in Agr.)	Day Labourer (in Agr.)	Employer (in Agr.)	Self-Employed (in Agr.)
period=2001 × treatment	0.021 (0.032)	-0.004 (0.006)	-0.015 (0.032)	-0.041 (0.032)	-0.007 (0.012)	-0.009 (0.021)	0.003 (0.008)	-0.016 (0.029)
period=2002 × treatment	-0.005 (0.026)	0.002 (0.005)	0.006 (0.027)	-0.020 (0.033)	-0.005 (0.008)	-0.043** (0.021)	0.003 (0.006)	0.001 (0.033)
period=2003 × treatment	0.003 (0.041)	0.012 (0.008)	-0.013 (0.041)	0.008 (0.036)	-0.012 (0.011)	-0.024 (0.029)	0.006 (0.008)	0.031 (0.031)
period=2011 × treatment	0.000 (0.031)	-0.010 (0.006)	0.007 (0.031)	0.071* (0.042)	0.003 (0.014)	0.036 (0.029)	0.001 (0.005)	0.078** (0.038)
period=2012 × treatment	0.001 (0.031)	-0.003 (0.005)	0.014 (0.029)	0.054 (0.051)	-0.003 (0.012)	-0.017 (0.038)	-0.001 (0.005)	0.085* (0.046)
period=2013 × treatment	0.002 (0.026)	-0.007* (0.004)	0.010 (0.027)	0.057 (0.044)	-0.008 (0.013)	-0.016 (0.024)	0.002 (0.004)	0.069* (0.037)
period=2014 × treatment	0.015 (0.032)	-0.003 (0.005)	0.003 (0.027)	0.053 (0.052)	-0.015 (0.014)	0.015 (0.029)	0.001 (0.005)	0.100** (0.046)
period=2015 × treatment	-0.021 (0.028)	0.004 (0.005)	0.014 (0.028)	0.062 (0.040)	0.015 (0.017)	0.004 (0.024)	0.002 (0.004)	0.059 (0.041)
period=2016 × treatment	-0.053** (0.023)	0.003 (0.004)	0.042** (0.021)	0.101** (0.046)	0.021 (0.019)	0.035 (0.031)	0.003 (0.005)	0.077* (0.042)
Mean	0.399	0.013	0.564	0.260	0.023	0.094	0.008	0.167
R-squared	0.14	0.10	0.12	0.33	0.14	0.20	0.08	0.32
N. of obs	1161	1161	1161	1161	1161	1161	1161	1161

Notes The unit of observation is the individual. All regressions include fixed effects for each year and each UPM (Primary Sample Unit), which corresponds to a populated places. Standard errors are clustered at the UPM level. Statistical significance levels: \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

## 8 Conclusions

Can the increase in demand for organic certified products in developed countries be one of the causes of emigration from developing to developed countries? I hypothesize that the expansion of organic farming, due to organic certifications, in export-oriented agriculture sectors in developing countries made crops more vulnerable to infectious plant diseases. Consistent with the hypothesis of a negative income elasticity of emigration, the spread of the disease created an unexpected negative income shock to producers and a push factor to migrate towards more developed countries. I empirically investigate this research question by studying the coffee leaf rust (CR) epidemic that hit the coffee sector in Central America in 2012/13. I find causal evidence in Guatemala by leveraging an IV strategy, that exploits the variation in distance of coffee farms to the first "as good as random" wave of organic certified cooperatives in the country, assuming that the diffusion of organic certifications happens by word of mouth. I find that a 1 SD increase in the share of organic farms in a given municipality led to 40% increase in the infection rate from CR and a 50% increase in the emigration rate in the same municipality. This evidence suggests that national organic programs and certification bodies should inform farmers about the possible unintended negative economic consequences of organic agriculture.

## References

- Angelucci, Manuela (2015). “Migration and financial constraints: Evidence from Mexico”. In: *Review of Economics and Statistics* 97.1, pp. 224–228.
- Avelino, Jacques, Laetitia Willocquet, and Serge Savary (2004). “Effects of crop management patterns on coffee rust epidemics”. In: *Plant pathology* 53.5, pp. 541–547.
- Avelino, Jacques et al. (2006). “The intensity of a coffee rust epidemic is dependent on production situations”. In: *Ecological modelling* 197.3-4, pp. 431–447.
- Avelino, Jacques et al. (2015). “The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions”. In: *Food Security* 7.2, pp. 303–321.
- Bacon, Christopher M et al. (2008). “Are sustainable coffee certifications enough to secure farmer livelihoods? The millenium development goals and Nicaragua’s Fair Trade cooperatives”. In: *Globalizations* 5.2, pp. 259–274.
- Bazzi, Samuel (2017). “Wealth heterogeneity and the income elasticity of migration”. In: *American Economic Journal: Applied Economics* 9.2, pp. 219–55.
- Bertoli, Simone, J Fernández-Huertas Moraga, and Francesc Ortega (2013). “Crossing the border: Self-selection, earnings and individual migration decisions”. In: *Journal of Development Economics* 101, pp. 75–91.
- Beuchelt, Tina D and Manfred Zeller (2011). “Profits and poverty: Certification’s troubled link for Nicaragua’s organic and fairtrade coffee producers”. In: *Ecological Economics* 70.7, pp. 1316–1324.
- Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak (2014). “Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh”. In: *Econometrica* 82.5, pp. 1671–1748.
- Chiputwa, Brian, David J Spielman, and Matin Qaim (2015). “Food standards, certification, and poverty among coffee farmers in Uganda”. In: *World Development* 66, pp. 400–412.
- Clemens, Michael A (2014). “Does development reduce migration?” In: *International handbook on migration and economic development*.
- Donovan, Jason and Nigel Poole (2014). “Changing asset endowments and smallholder participation in higher value markets: Evidence from certified coffee producers in Nicaragua”. In: *Food Policy* 44, pp. 1–13.

- Dragusanu, Raluca and Nathan Nunn (2018). *The effects of Fair Trade certification: evidence from coffee producers in Costa Rica*. Tech. rep. National Bureau of Economic Research.
- Facchini, Giovanni and Anna Maria Mayda (2009). “Does the welfare state affect individual attitudes toward immigrants? Evidence across countries”. In: *The review of economics and statistics* 91.2, pp. 295–314.
- Haggar, Jeremy et al. (2017). “Environmental-economic benefits and trade-offs on sustainably certified coffee farms”. In: *Ecological Indicators* 79, pp. 330–337.
- Harris, Ian et al. (2020). “Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset”. In: *Scientific data* 7.1, pp. 1–18.
- Heldring, Leander (2021). “The origins of violence in Rwanda”. In: *The Review of Economic Studies* 88.2, pp. 730–763.
- McKenzie, David and Hillel Rapoport (2007). “Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico”. In: *Journal of development Economics* 84.1, pp. 1–24.
- Merle, Isabelle et al. (2020). “Unraveling the Complexity of Coffee Leaf Rust Behavior and Development in Different Coffea arabica Agroecosystems”. In: *Phytopathology* 110.2, pp. 418–427.
- Özak, Ömer et al. (2012). *Distance to the technological frontier and economic development*. Tech. rep.
- Pham, Yen et al. (2019). “The impact of climate change and variability on coffee production: a systematic review”. In: *Climatic Change* 156.4, pp. 609–630.
- Rogall, Thorsten (2021). “Mobilizing the masses for genocide”. In: *American economic review* 111.1, pp. 41–72.
- Stock, James H and Motohiro Yogo (2002). *Testing for weak instruments in linear IV regression*.



# Appendix

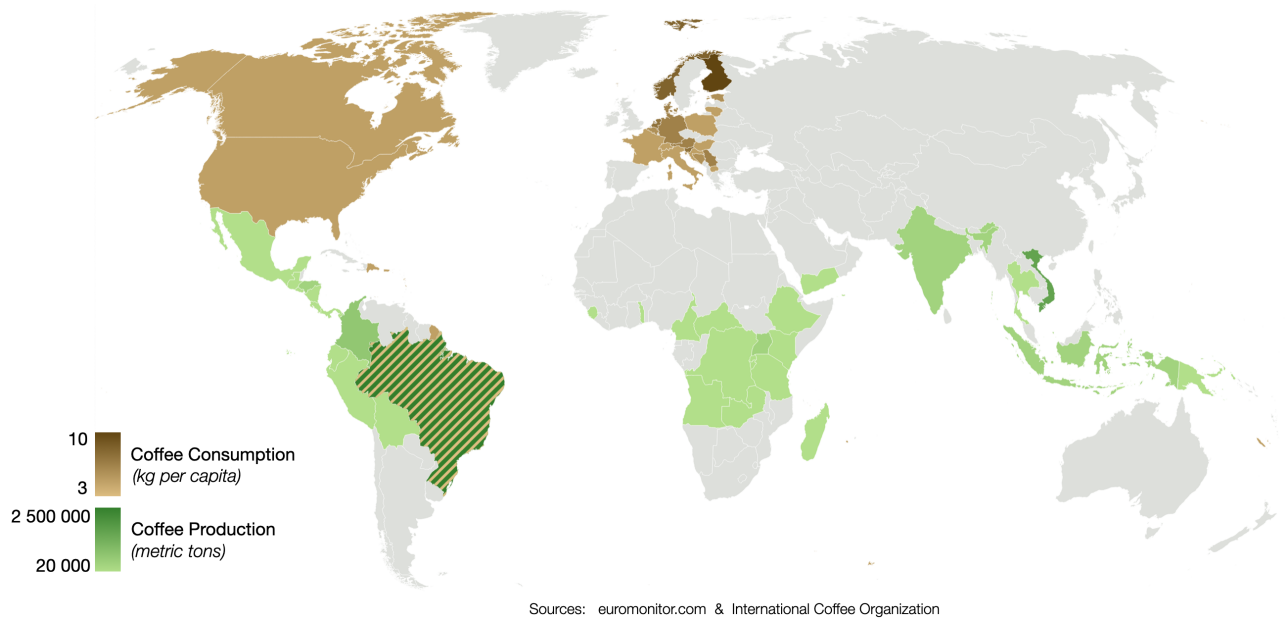


Figure 9: Top coffee producers and consumers in the world

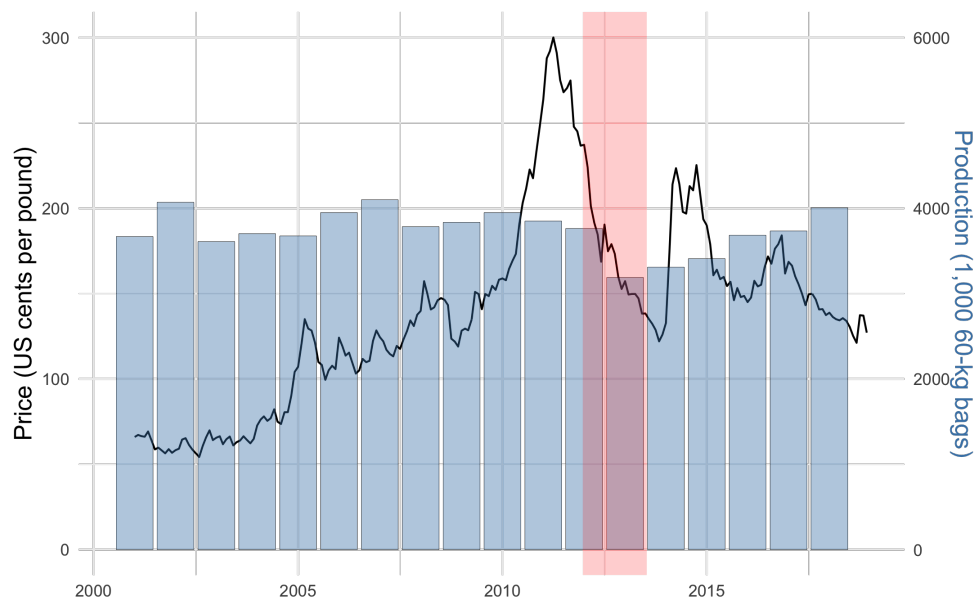


Figure 10: Time Variation in Coffee's Price and Production

# Results Report: Interview with Coffee Growers on Coffee Leaf Rust

Project: Coffee Rust: Unintended Consequences of Organic/Bio Certifications

Country: Guatemala

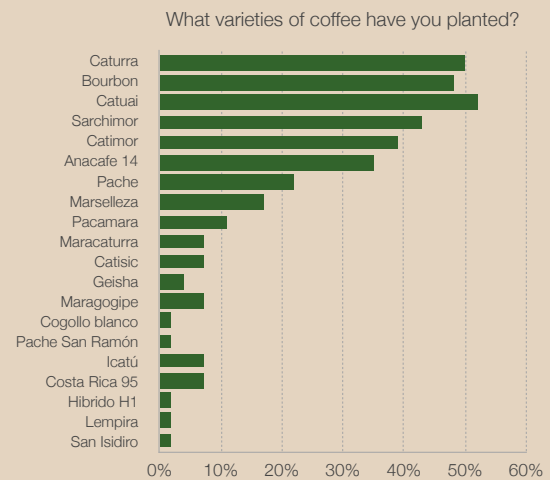
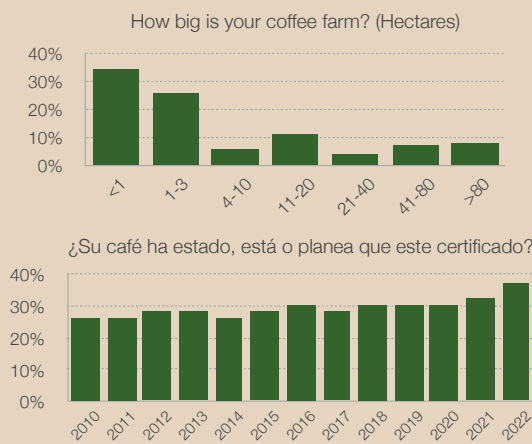
Municipalities: Nueva Santa Rosa, Mataquescuintla, Acatenango, Sololá, Colomba

Number of interviews: 46

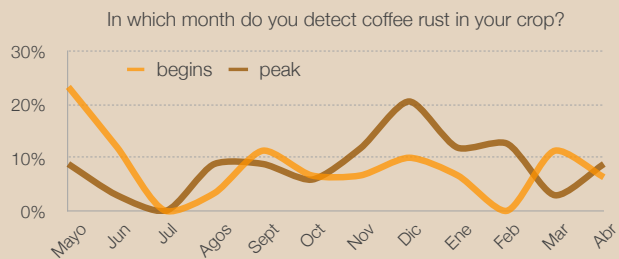
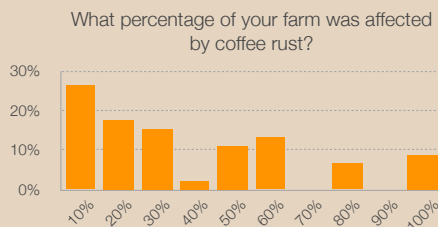
Date: December 2021



## Characteristics of Coffee Farms:



## Coffee Leaf Rust Monitoring (2020/2021 season):



## Preventive Measures against Coffee Leaf Rust:

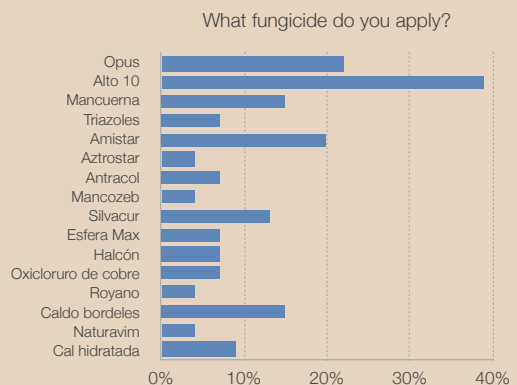
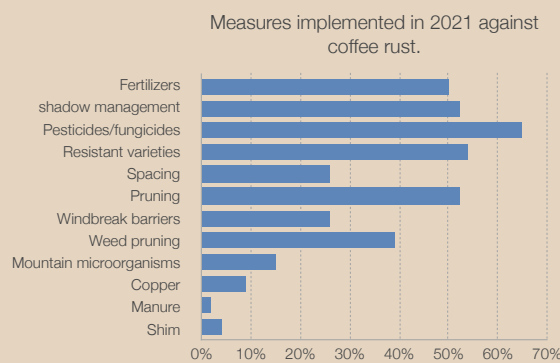


Figure 11: Report from the Field (page 1)

Quotes from Focus Groups:

Do you think that the coffee rust in the region (not in your plot) could affect your plantation? How?

*"It is alarming because, if the neighbour already has the rust, it affects me."*

*"If the neighbour's coffee plantation is full of rust, we carry the dust on our clothes and when we enter our coffee plantation, we contaminate it."*

*"If the neighbour is full of rust and he doesn't worry about it, it's going to create a problem, as the air is going to bring us rust."*

Do you coordinate with your neighbours when you apply fungicide? How?

*"Cooperatives train us for the application of pesticides, but the timing is up to each one of us."*

*"Here we understand that each one has their own different management. The problem is that there is no coordination."*

*"The rust attack is strong because we never agree, we do not spray at the same time."*

What are the advantages and/or disadvantages of fumigating?

*"What we did was to change varieties, however, the rust is still present: the only thing left to do is fumigate."*

*"In the end, all we want is to produce and that the plant is healthy. I don't care if it is organic or not."*

*"With rust everything is preventive, there is no cure."*

*"My experience is that if I want to eliminate a disease, I must prevent it from spreading, remove it when it is small."*

Do you think the coffee rust problem can be solved? who should be responsible?

*"There has to be help from the central government."*

*"The problem is that the support (from the government) is not permanent."*

*"A monitoring system is needed in the prevention stage."*

*"It would be good to have a training to see which fungicide is less harmful and is more effective to combat the rust."*

Principal investigator:

**EMILIO DAL RE**

PhD student in economics,  
University of Zurich (Switzerland)

Collaborating institutions:



Implementation team:



ERICK RENÉ LÓPEZ DE PAZ &  
ANA ROCÍO SILVA RIVERA

Research funded by:



Figure 12: Report from the Field (page 2)

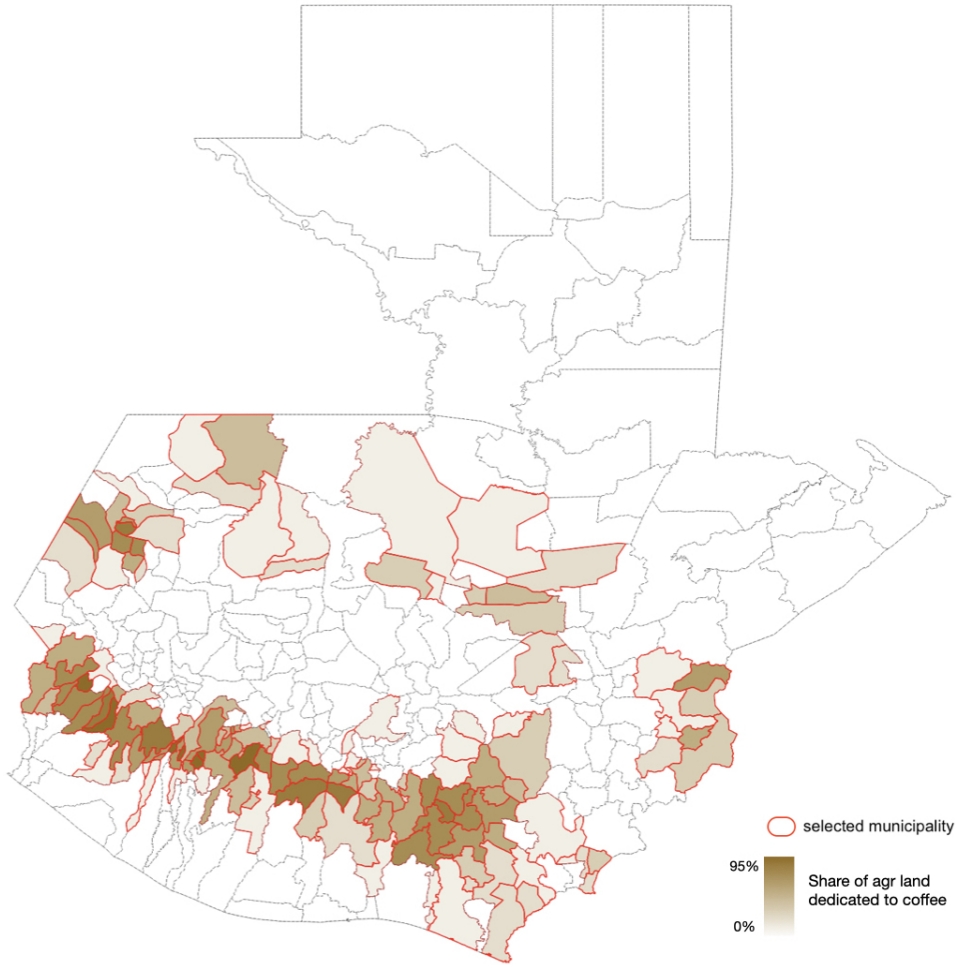


Figure 13: Selected Municipalities

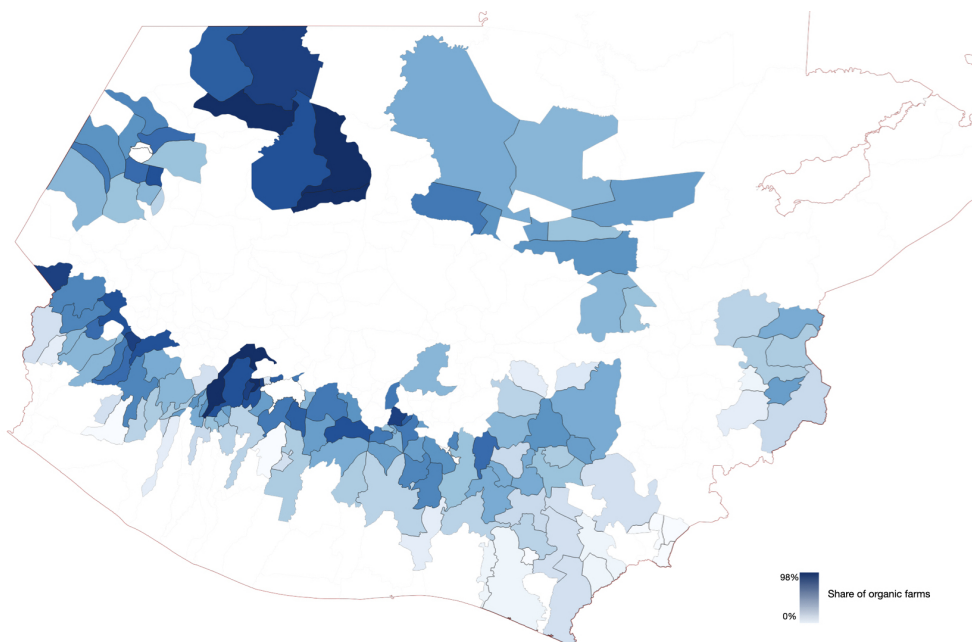


Figure 14: Share of Organic Coffee Farms

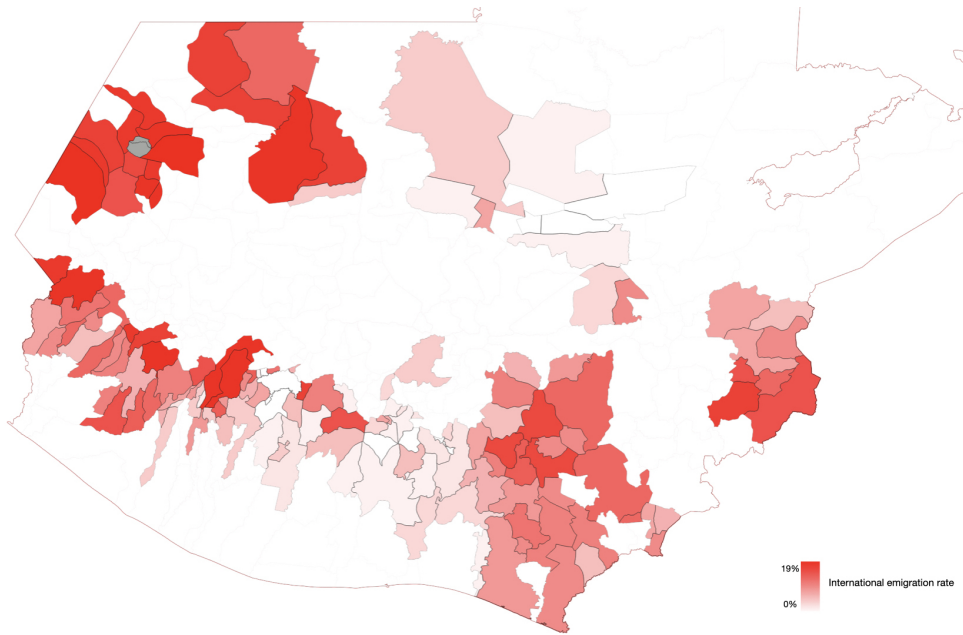


Figure 15: Emigration Rate

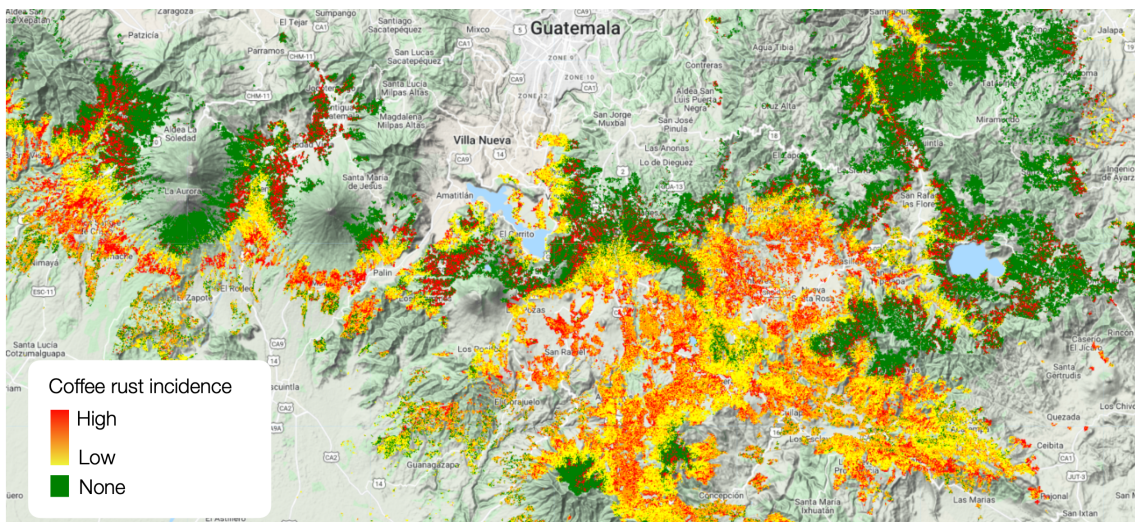
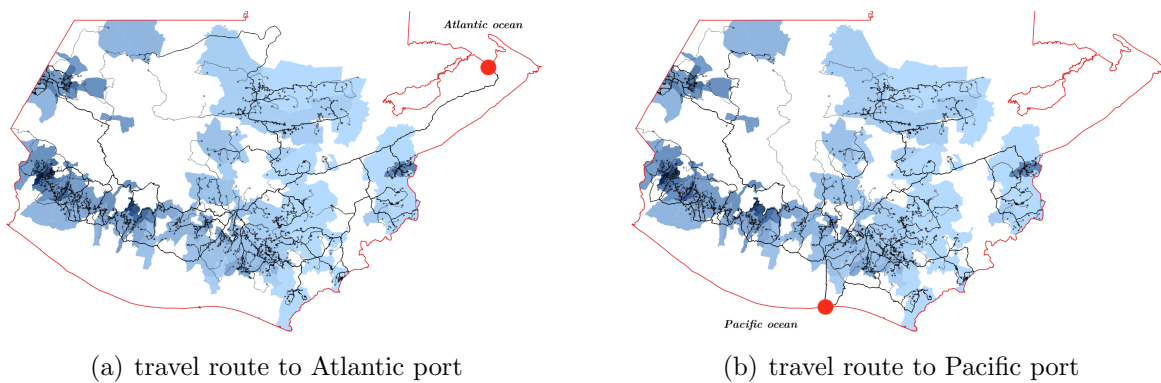


Figure 16: Coffee Rust

Figure 17: Market Access Routes



(a) travel route to Atlantic port

(b) travel route to Pacific port

Table 11: 2SLS Estimation of Main Effect

Dependent Variable:	Emigration Share					
	(1)	(2)	(3)	(4)	(5)	(6)
organic_share_3_SD	0.004 (0.003)	0.012*** (0.004)	0.007*** (0.002)	0.007** (0.003)	0.006** (0.003)	0.006* (0.003)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.01	0.01	0.01	0.01	0.01	0.01
R-squared	0.03	-0.24	0.67	0.74	0.76	0.78
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The emigration share is computed as the share of households that had at least one member who emigrated after 2013. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

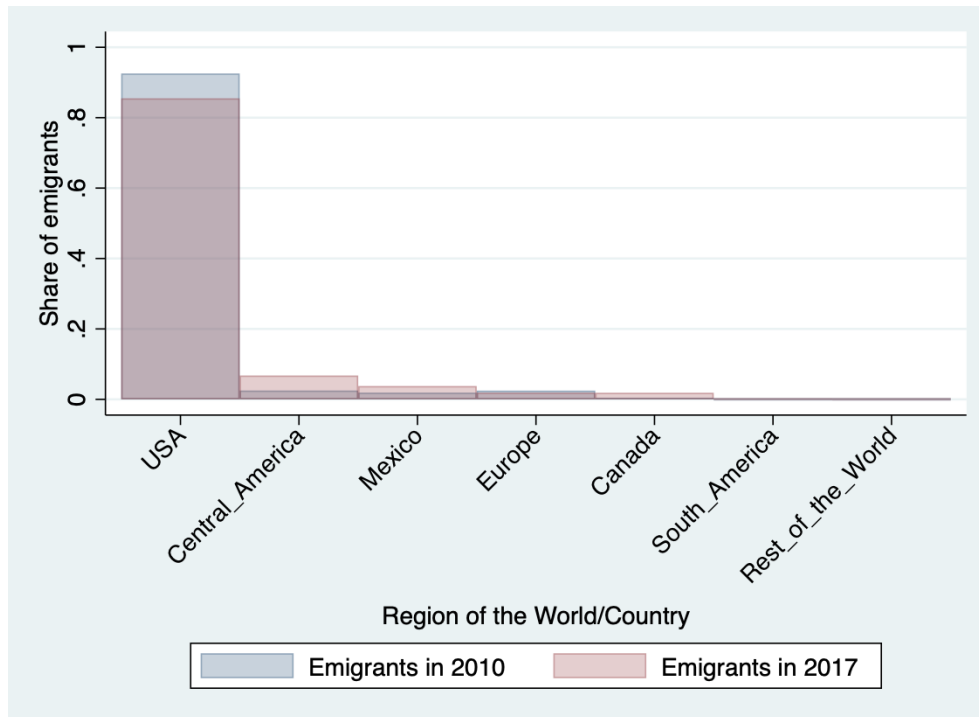


Figure 18: emigration by destination country

Table 12: 2SLS Estimation of Main Effect: Urban Areas

Dependent Variable:	Emigration Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Share (SD)	0.027*	0.024	0.027	0.017	0.013	0.012
	(0.016)	(0.025)	(0.022)	(0.026)	(0.015)	(0.016)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.04	0.19	0.72	0.78	0.80	0.81
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The emigration rate is referred to the population 15-65 years old. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 13: 2SLS Estimation of Main Effect: Pre Coffee Rust

Dependent Variable:	Emigration Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Share (SD)	0.017	0.014	0.007	0.007	0.003	0.002
	(0.016)	(0.025)	(0.022)	(0.026)	(0.015)	(0.016)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.04	0.19	0.72	0.78	0.80	0.81
N. of obs	142	142	142	142	142	142

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The emigration rate is referred to the population 15-65 years old. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 14: 2SLS Estimation of Main Effect: Areas with No Coffee Production

Dependent Variable:	Emigration Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Share (SD)	0.017 (0.016)	0.014 (0.025)	0.012 (0.022)	0.011 (0.016)	0.008 (0.009)	0.008 (0.010)
lagged dep var	no	no	yes	yes	yes	yes
Geo controls	no	no	no	yes	yes	yes
Agr controls	no	no	no	no	no	yes
SEC controls	no	no	no	no	yes	yes
regional FE	no	yes	yes	yes	yes	yes
mean	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.04	0.19	0.72	0.78	0.80	0.81
N. of obs	152	152	152	152	152	152

*Notes* The unit of observation is a municipality. All control variables are measured in SD. The emigration rate is referred to the population 15-65 years old. The instrument is the average distance to the first 3 cooperatives certified organic before 2006. Lagged dependent variables are defined as the outcome variable, but over the 10-6 years and 5-1 year span before 2013. Geographical controls include the average altitude, the squared average altitude, the distance to the capital, market access, and size of the municipality. Agricultural controls are the share of coffee farms that use irrigation, the total number of coffee farms, and the share of agricultural land dedicated to coffee. Socio Economic Characteristics controls include the literacy rate, the share of population economically active and the total number of households. Robust standard errors are in parentheses. Statistical significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .