The Effect of Maquiladoras on Mexican Entrepreneurship

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Summer 2021

Introduction

What are maquiladoras?

- Foreign-run manufacturing plants in Latin America that create products for export.
- The concept was created by the Mexican government in 1965 to help industrialize northern Mexico.
- The program is designed to attract foreign business investment in Mexico.
- Example companies that have operated maquiladoras:

CorpWatch, 1999
Ivemsa, 2019
The City of San Diego, 2016

What are the benefits of maquiladoras for companies?

- Lower labor costs
  - “approximately $15-16/day for basic operators
  - $42/day for technicians
  - 100/day for engineers”
- Nearshoring allows companies to set up operations in a foreign country that’s closer to visit, in the same time zone, and incur lower shipping costs.
- Mexico exempts maquiladoras from the 16% VAT on imports
- Maquiladoras have the ability to circumvent duties on imported raw materials.
- Companies can operate their maquiladora under a shelter service to reduce liability.
- Fewer environmental regulations

Ivemsa, 2019
Tetakawi, 2020

What are the benefits of maquiladoras for people?

- New employment opportunities
- Brings foreign exchange into Mexico
- According to some studies:
  - Manufacturing and managerial tasks are transferred to local companies.
  - Technical and managerial skills transfer to local firms.

Contreras et al., 2012

Hypothesis: “The introduction of maquiladoras into Mexico spurs entrepreneurship, marked by the formation of new businesses.”

Data Cleaning

Datasets

- Solunet-infomex.com Dataset
  - Solunet-infomex.com is an industrial listing website.
  - Data points for each maquiladora by year (2005, 2006, 2007, 2008, 2009, 2011)
  - Includes factory information like:
    - plant type
    - product being manufactured
    - parent company name
    - parent company location
    - plant address, plant city, plant state

Datasets

- Founders Dataset
  - From INEGI — Mexico's National Institute of Statistics and Geography
  - Data points for each municipality by year
  - Includes:
    - average income
    - total population
    - number of new foundings
    - drug rate
    - homicide rate
    - foreign direct investment
    - number of people self employed
    - next to border or not

Cleaning process

- Match 3-letter Solunet state codes with official state codes

	code	state
0	SLP	San Luis Potosi
1	JAL	Jalisco
2	SON	Sonora
3	CHI	Chihuahua
4	NUL	Nuevo Leon
5	TAM	Tamaulipas
6	BCN	Baja California
7	MEX	Mexico
8	DUR	Durango
9	DIF	Ciudad de Mexico
10	COA	Coahuila de Zaragoza
11	AGU	Aguascalientes
12	QUE	Queretaro
13	PUE	Puebla
14	SIN	Sinaloa
15	YUC	Yucatan

Name of federative entity	Conventional abbreviation	2-letter code*	3-letter code (ISO 3166-2:MX)
Aguascalientes	Ags.	MX - AG	MX-AGU
Baja California	B.C.	MX - BC	MX-BCN
Baja California Sur	B.C.S.	MX - BS	MX-BCS
Campeche	Camp.	MX - CM	MX-CAM
Chiapas	Chis.	MX - CS	MX-CHP
Chihuahua	Chih.	MX - CH	MX-CHH
Coahuila	Coah.	MX - CO	MX-COA
Colima	Col.	MX - CL	MX-COL
Mexico City	CDMX	MX - DF	MX-CMX
Durango	Dgo.	MX - DG	MX-DUR
Guanajuato	Gto.	MX - GT	MX-GUA
Guerrero	Gro.	MX - GR	MX-GRO
Hidalgo	Hgo.	MX - HG	MX-HID
Jalisco	Jal.	MX - JA	MX-JAL
México	Edomex. or Méx.	MX - EM	MX-MEX
Michoacán	Mich.	MX - MI	MX-MIC
Morelos	Mor.	MX - MO	MX-MOR
Nayarit	Nay.	MX - NA	MX-NAY
Nuevo León	N.L.	MX - NL	MX-NLE

The solunet code is not the same always the same as the ISO code.

For Nuevo León:
Solunet code is NUL
ISO code is NLE

Cleaning process

- Fix incorrect state labels
    - Some Baja California Sur cities like La Paz were incorrectly labelled Baja California
- Get INEGI municipality codes and add to the Solunet dataset

	state	city	mexmuncode
0	Aguascalientes	Aguascalientes	1001
1	Aguascalientes	Asientos	1002
2	Aguascalientes	Calvillo	1003
3	Aguascalientes	Cosio	1004
4	Aguascalientes	Jesus Maria	1005
...	...	...	...
2497	Zacatecas	Zacatecas	32056
2498	Zacatecas	Trancoso	32057
2499	Zacatecas	Santa Maria de la Paz	32058
2500	Zacatecas	Municipio no especificado	32999
2501	Entidad no especificada	Municipio no especificado	999999

Cleaning process

- After this 2,857 maquiladoras were still not properly labelled with an INEGI code
- Fixed differences in naming conventions between INEGI and Solunet

Cleaning process

- Many of the unmatched codes were from Mexico City.
    - Some maquiladoras were labelled with Mexico City instead of the municipalities inside.
- I used the Google Maps Geocoding API to get the municipality from the maquiladora address

```python
from geopy.geocoders import GoogleV3
geolocator = GoogleV3(api_key='', user_agent="maquiladora_research")
location = geolocator.geocode("Magdalena No. 226 Ciudad de Mexico")
print(location.address)
print('\n')
print(location.raw)
```

```
Mexico City, CDMX, Mexico


{'address_components': [{'long_name': 'Mexico City', 'short_name': 'México D.F.', 'types': ['locality', 'political']}, {'long_name': 'Mexico City', 'short_name': 'CDMX', 'types': ['administrative_area_level_1', 'political']}, {'long_name': 'Mexico', 'short_name': 'MX', 'types': ['country', 'political']}], 'formatted_address': 'Mexico City, CDMX, Mexico', 'geometry': {'bounds': {'northeast': {'lat': 19.5927571, 'lng': -98.9604482}, 'southwest': {'lat': 19.1887101, 'lng': -99.3267771}}, 'location': {'lat': 19.4326077, 'lng': -99.133208}, 'location_type': 'APPROXIMATE', 'viewport': {'northeast': {'lat': 19.5927571, 'lng': -98.9604482}, 'southwest': {'lat': 19.1887101, 'lng': -99.3267771}}}, 'partial_match': True, 'place_id': 'ChIJB3UJ2yYAzoURQeheJnYQBlQ', 'types': ['locality', 'political']}
```

Cleaning process

- After running the API, 1,329 maquiladoras did not have specified municipalities.
- Of these, there were 77 unique city names in the Solunet dataset that did not match any municipalities associated with INEGI municipality codes.
- I manually corrected all of these.

```
'Santa Rosa Jauregui': 'Queretaro', 'Parral': 'Hidalgo del Parral', 'Obregon': 'Cajeme', 'Rosarito': 'Playas de Rosarito',
'Cienaga de Flores': 'Cienega de Flores', 'Garza Garcia': 'San Pedro Garza Garcia', 'Ciudad Apodaca': 'Apodaca',
'San Nicolas De Los Garza': 'San Nicolas de los Garza', 'Escobedo': 'General Escobedo', 'J. Gomez Portugal': 'Jesus Maria',
'Playas Rosarito': 'Playas de Rosarito', 'Puerto Adolfo Lopez Mateos': 'Comondu', 'Ciudad Insurgentes': 'Comondu',
'Cabo San Lucas': 'Los Cabos', 'Santa Rosalia': 'Mulege', 'Puerto Palomas': 'Ascension', 'Nueva Rosita': 'San Juan de Sabinas',
'Taxco': 'Taxco de Alarcon', 'Tulancingo': 'Tulancingo de Bravo', 'Pachuca': 'Pachuca de Soto', 'Guzman': 'Zapotlan el Grande',
'Tlaquepaque': 'San Pedro Tlaquepaque', 'Apulco': 'Tuxcacuesco', 'Ecatepec': 'Ecatepec de Morelos',
'Garza Garcia': 'San Pedro Garza Garcia', 'San Jose Munive, Huejotzingo': 'Huejotzingo', 'Amealco': 'Amealco de Bonfil',
'Juriquilla': 'Queretaro', 'Cancun': 'Benito Juarez', 'Fernandez': 'Ciudad Fernandez', 'Rio Verde': 'Rioverde',
'Escalerillas': 'San Luis Potosi', 'Los Mochis': 'Ahome', 'Aztecas': 'Ahome', 'Ciudad Obregon': 'Cajeme', 'Mante': 'El Mante',
'Ciudad Victoria': 'Victoria', 'Ciudad Mante': 'Mante', 'Tetla': 'Tetla de la Solidaridad', 'Calera Victor Rosales': 'Calera'
```

Cleaning process

- This left 143 maquiladora data points without a municipality code.
- Of these, there were 2 states that did not match INEGI official names.
  - 'Michoacan', 'Veracruz'
- I fixed these, leaving 82 maquiladora data points unaccounted for.
  - ‘Michoacan de Ocampo’, ‘Veracruz’
- After another check, 14 more cities needed their names fixed.

```
'tepeji de ocampo': 'tepeji del rio de ocampo', 'cuautepec': 'cuautepec de hinojosa',
'tultitlan de mariano escobedo': 'tultitlan', 'san jose el alto': 'queretaro',
'santiago de queretaro': 'queretaro', 'mante': 'el mante', 'jalapa': 'xalapa', 'tejeria': 'veracruz'
```

Cleaning process

- Now, there were 44 maquiladoras with 21 unique addresses that did not have a corresponding INEGI municipality code.
- For good measure, I manually searched the addresses and verified if there was a factory there.
- This left only 34 data points out of 14,976

Combining Datasets

- Now that both the Solunet and Foundings datasets have INEGI municipality codes, I can merge the two datasets.
- I created a variable for maquiladora count per municipality per year and added it to the foundings data.
- Now I have maquiladora information at the municipal/year level.

Exploratory Data Analysis

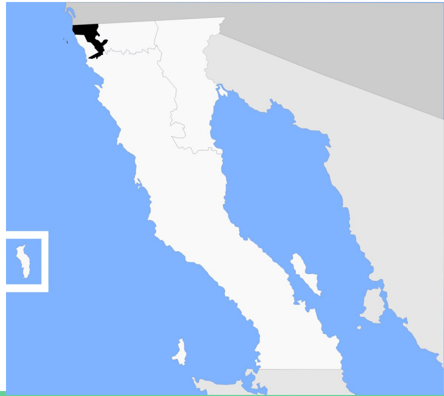
Exploratory Data Analysis

Data per municipality per year:

Mean number of maquiladoras: 1.044

Median number of maquiladoras: 0.000

Tijuana had the maximum number of maquiladoras (523) in 2005.



Exploratory Data Analysis

Data per municipality per year:

Total number of new firm foundings: 568,388

Mean number of new firm foundings: 39.937

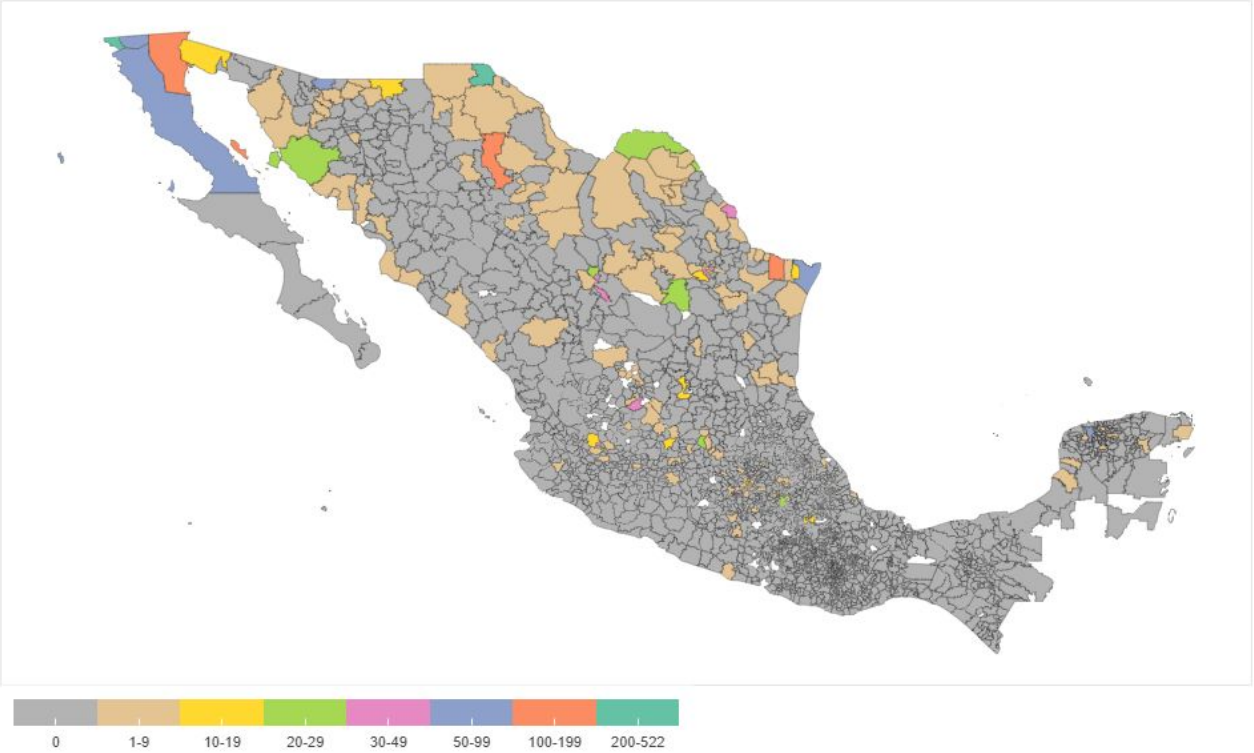
Median number of new firm foundings: 0.0

Guadalajara had the maximum number of new firm foundings (8524) in 2005

In that 2005, Guadalajara had 38 maquiladoras.

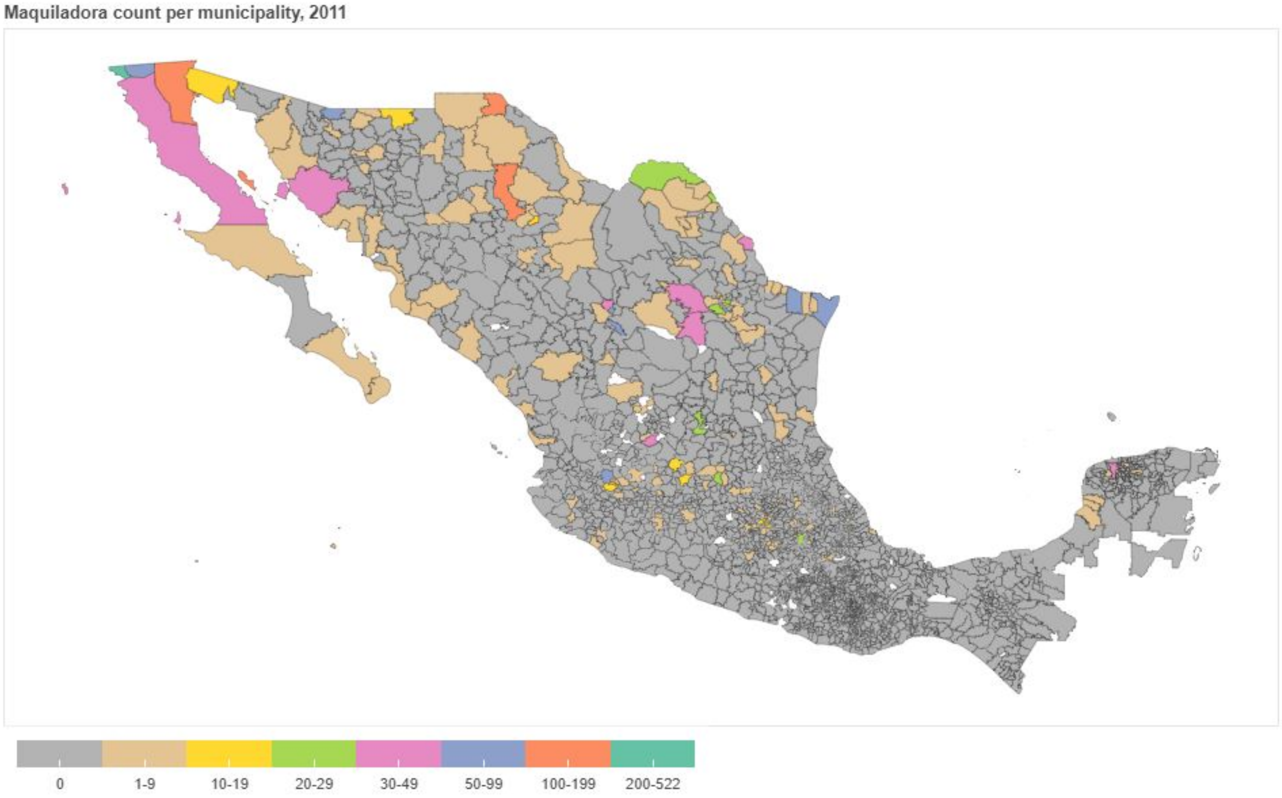
Exploratory Data Analysis

Maquiladora count per municipality, 2005



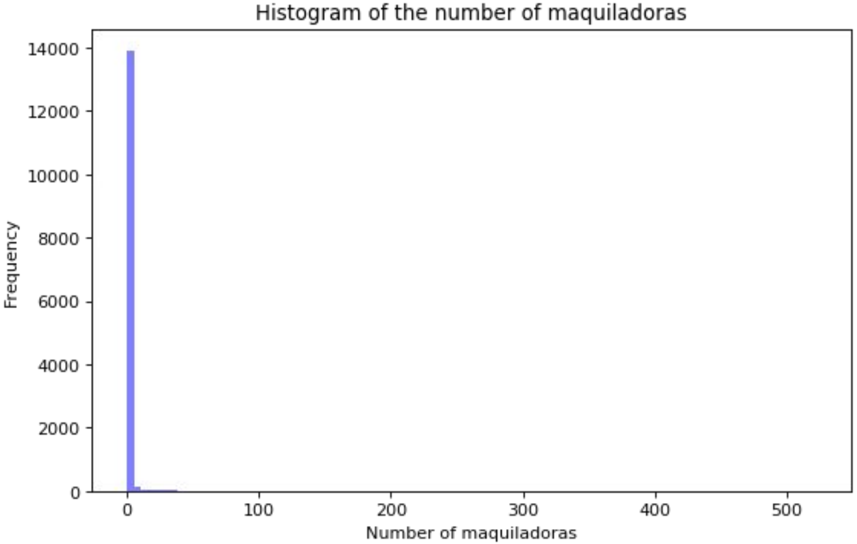
2479 total maquiladoras in 2005

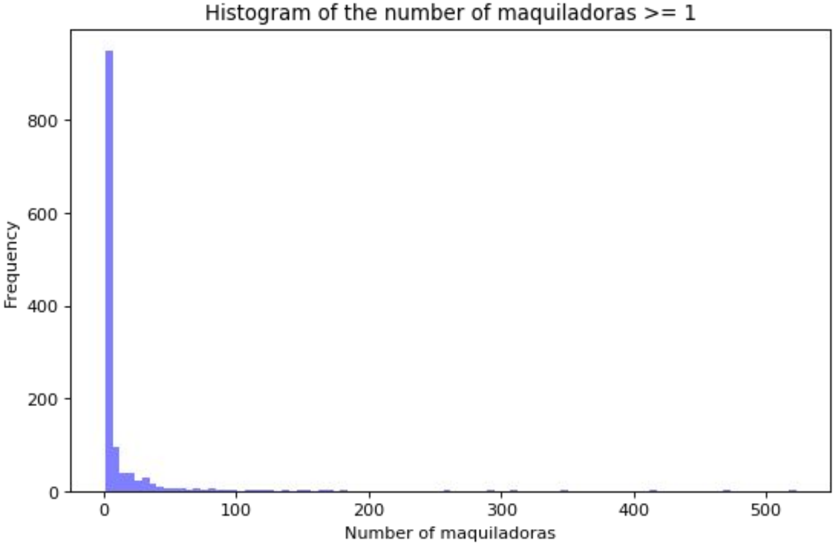
Exploratory Data Analysis



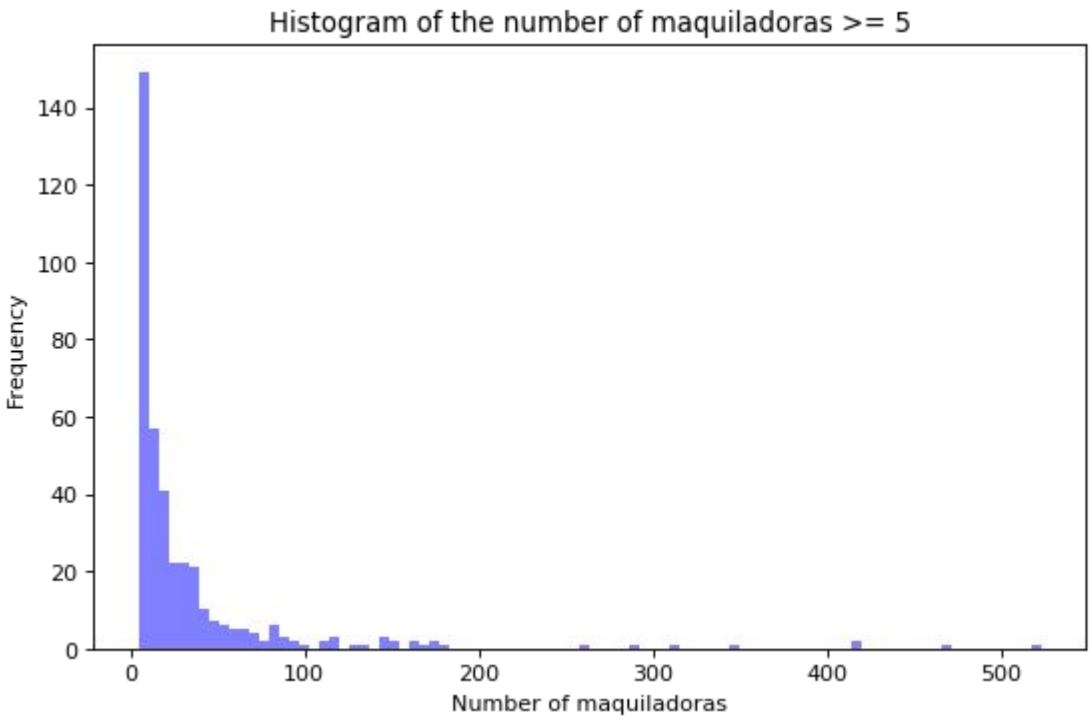
2558 total maquiladoras in 2011

Exploratory Data Analysis

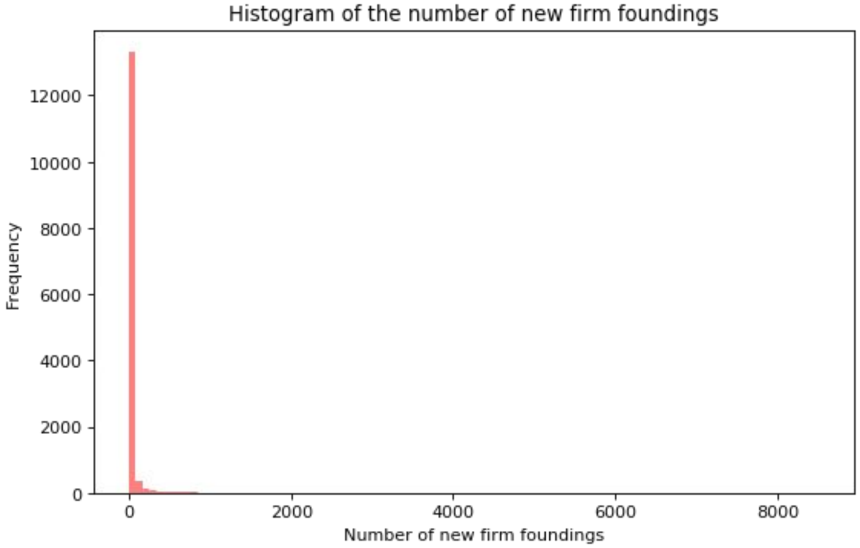


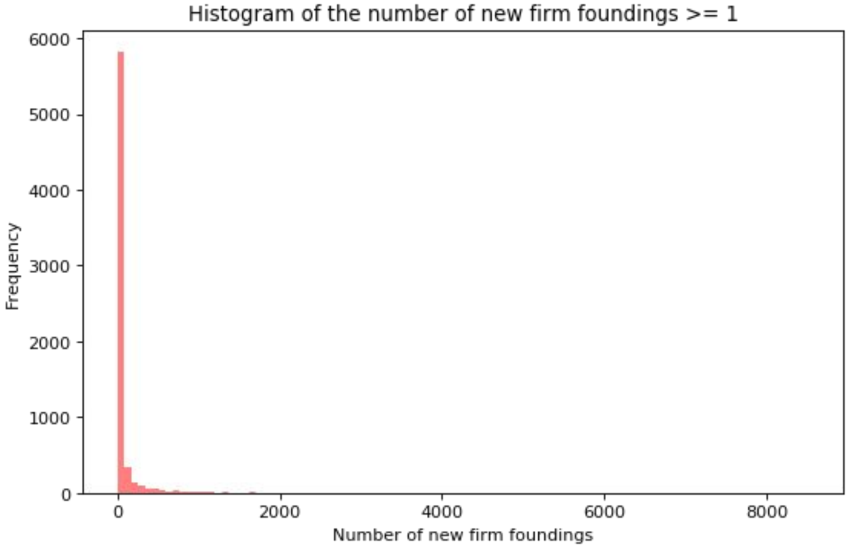


Exploratory Data Analysis

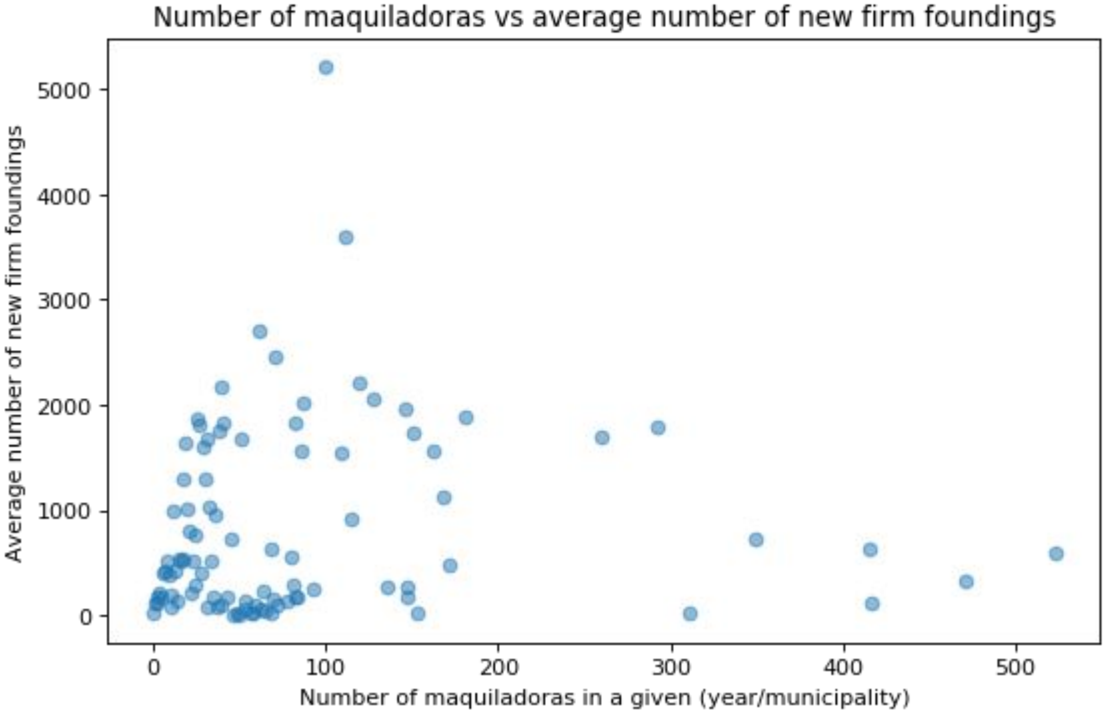


Exploratory Data Analysis

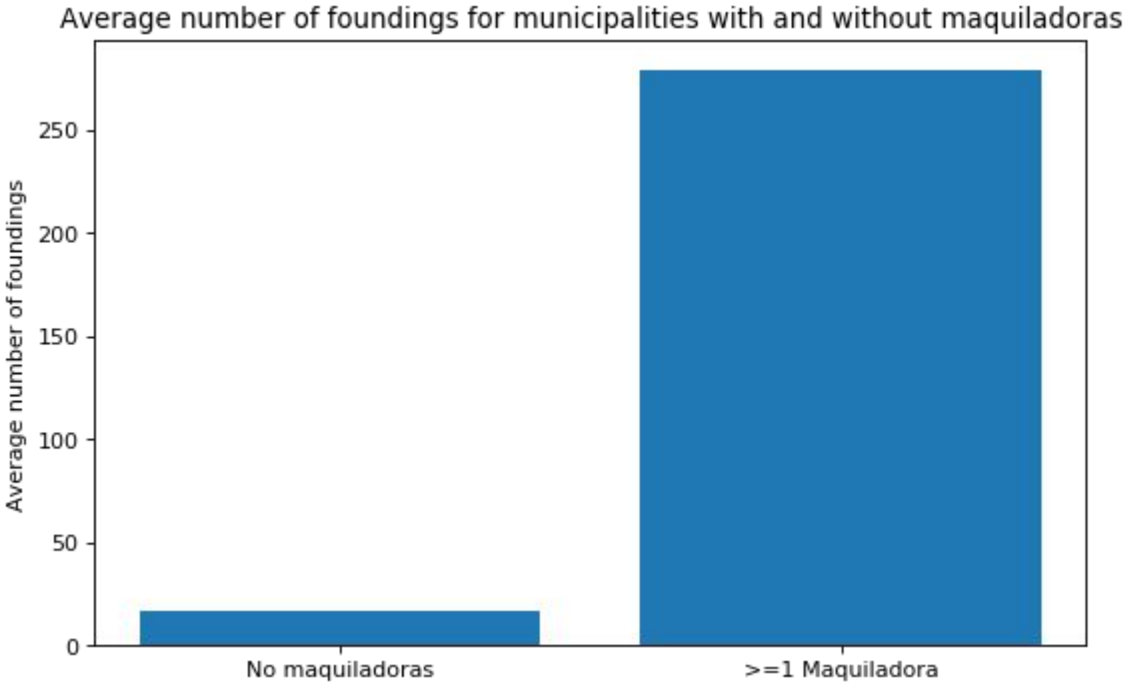




Exploratory Data Analysis



Exploratory Data Analysis



Analyses

Negative binomial regression

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
maquiladora_~t	1.177095	.0112206	17.10	0.000	1.155307	1.199294
_cons	22.71904	.6103606	116.25	0.000	21.55371	23.94738
/lnalpha	2.176763	.0138433			2.149631	2.203896
alpha	8.81772	.1220661			8.581692	9.060241

Without accounting for confounding variables, for every additional maquiladora, there is a 17.71% increase on average in the number of new foundings.

Negative binomial regression

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
maquiladora_~t	1.020284	.0021238	9.65	0.000	1.016129	1.024455
ptotal	920.3836	357.0565	17.59	0.000	430.2799	1968.732
gini	68.71097	37.05901	7.84	0.000	23.87447	197.7509
rate_drug	.9976823	.0004679	-4.95	0.000	.9967657	.9985998
lincome	10.2606	.5608882	42.59	0.000	9.218121	11.42097
border	.214059	.0491651	-6.71	0.000	.1364675	.3357667
fdi	1.00018	.0000225	8.00	0.000	1.000136	1.000224
homicidespc	0	0	-12.02	0.000	0	0
year						
2006	1.097333	.0704155	1.45	0.148	.9676469	1.244399
2007	1.416462	.0858213	5.75	0.000	1.257859	1.595064
2008	1.600617	.0955528	7.88	0.000	1.423878	1.799293
2009	1.642398	.1004904	8.11	0.000	1.456792	1.851652
2011	1	(omitted)				
_cons	5.13e+71	1.27e+73	6.68	0.000	4.56e+50	5.76e+92
/lnalpha	1.659224	.0150182			1.629789	1.688659
alpha	5.255233	.0789241			5.102799	5.41222

For every additional maquiladora, there is a 2.03% increase in the number of foundings on average.

Negative binomial regression with 1 year lag

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
lag1	1.025803	.0027987	9.34	0.000	1.020332	1.031303
ptotal	471.5687	211.8301	13.70	0.000	195.5161	1137.384
gini	1206.477	803.7547	10.65	0.000	326.9256	4452.35
rate_drug	.9978144	.0005898	-3.70	0.000	.996659	.9989711
lincome	10.74772	.7189911	35.50	0.000	9.427003	12.25348
border	.16129	.0458239	-6.42	0.000	.0924216	.2814759
fdi	1.000159	.000022	7.25	0.000	1.000116	1.000202
homicidespc	0	0	-12.77	0.000	0	0
year						
2007	1.227887	.0835092	3.02	0.003	1.074652	1.402972
2008	1.288585	.0876605	3.73	0.000	1.127736	1.472377
2009	1.205404	.0825847	2.73	0.006	1.053938	1.378638
_cons	5.11e-11	3.32e-11	-36.53	0.000	1.43e-11	1.82e-10
/lnalpha	1.618272	.0179662			1.583058	1.653485
alpha	5.044364	.0906281			4.869827	5.225156

For every additional maquiladora in the previous year, there is a 2.58% increase in the number of foundings on average.

Negative binomial regression with 2 year lag

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
lag2	1.025464	.0034121	7.56	0.000	1.018799	1.032174
ptotal	406.3717	211.4684	11.54	0.000	146.5459	1126.868
gini	6544.066	5696.976	10.09	0.000	1188.035	36046.77
rate_drug	.997809	.0005998	-3.65	0.000	.9966341	.9989852
lincome	10.9677	.8716771	30.13	0.000	9.385657	12.8164
border	.1420619	.0469579	-5.90	0.000	.0743219	.2715427
fdi	1.000148	.000026	5.70	0.000	1.000097	1.000199
homicidespc	0	0	-10.37	0.000	0	0
year						
2008	1.033101	.0701212	0.48	0.631	.9044153	1.180097
2009	.9909118	.0676205	-0.13	0.894	.8668589	1.132717
_cons	2.80e-11	2.23e-11	-30.55	0.000	5.90e-12	1.33e-10
/lnalpha	1.640398	.0207514			1.599726	1.68107
alpha	5.157221	.1070196			4.951675	5.3713

For every additional maquiladora 2 years earlier, there is a 2.55% increase in the number of foundings on average.

Negative binomial regression with municipal level fixed effects

```
Conditional FE negative binomial regression          Number of obs    =  9,198
Group variable: mexmuncode                           Number of groups =  1,533

                                                     Obs per group:
                                                                  min =      6
                                                                  avg =    6.0
                                                                  max =      6

                                                     Wald chi2(1)     =   5.40
Log likelihood = -22341.815                          Prob > chi2      = 0.0202

--------------------------------------------------------------------------------
      founding |        IRR   Std. err.      z    P>|z|     [95% conf. interval]
---------------+----------------------------------------------------------------
maquiladora_~t |   1.002145   .0009242     2.32   0.020     1.000335    1.003958
         _cons |   .9867092    .020771    -0.64   0.525     .9468271    1.028271
--------------------------------------------------------------------------------
```

maquiladora_count is statistically significant, but the constant is not

Negative binomial regression with municipal level fixed effects and a 1 year lag

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
lag1	1.001935	.0009949	1.95	0.051	.9999875	1.003887
_cons	1.531351	.0434138	15.03	0.000	1.448582	1.618849

lag1 is just barely not statistically significant.

Negative binomial regression with municipal level fixed effects and a 2 year lag

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
lag2	1.008085	.0011304	7.18	0.000	1.005872	1.010303
_cons	1.454188	.050091	10.87	0.000	1.359252	1.555754

For every additional maquiladora 2 years previously, there is a 0.8% increase in the number of foundings.

Negative binomial regression with municipal level fixed effects and a 2 year lag with other independent variables

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
lag2	1.007557	.0008875	8.55	0.000	1.005819	1.009298
ptotal	2.119578	.2941346	5.41	0.000	1.614834	2.782089
gini	61.15931	49.71997	5.06	0.000	12.43	300.922
rate_drug	.9977032	.0008671	-2.65	0.008	.9960052	.999404
lincome	8.12406	.59279	28.71	0.000	7.04147	9.373093
border	.2363764	.0567407	-6.01	0.000	.1476653	.3783815
fdi	1.000012	7.90e-06	1.53	0.125	.9999966	1.000028
homicidespc	1.79e-63	1.52e-61	-1.70	0.088	1.2e-135	2.64e+09
year						
2008	1.055536	.0274094	2.08	0.037	1.003158	1.110648
2009	.8281923	.0239288	-6.52	0.000	.7825959	.8764452
_cons	3.24e-10	2.39e-10	-29.60	0.000	7.62e-11	1.38e-09
/ln_r	-.6765219	.0324171			-.7400582	-.6129856
/ln_s	-.5609087	.0559204			-.6705106	-.4513067
r	.5083821	.0164803			.4770862	.5417311
s	.5706903	.0319132			.5114473	.6367955

For every additional maquiladora 2 years previously, there is a 0.76% increase in the number of foundings.

Population averaged poisson model with municipal level fixed effects and a 2 year lag with other independent variables

founding	IRR	Robust std. err.	z	P>|z|	[95% conf.	interval]
lag2	1.006315	.002738	2.31	0.021	1.000963	1.011696
ptotal	403.6717	1288.099	1.88	0.060	.7760351	209978.7
gini	2.97e+07	1.55e+08	3.30	0.001	1090.225	8.09e+11
fdi	.9999852	.0000127	-1.16	0.244	.9999603	1.00001
homicidespc	4.71e+60	8.33e+62	0.79	0.430	1.10e-90	2.0e+211
year						
2008	1.025074	.061919	0.41	0.682	.910624	1.15391
2009	.864584	.0694315	-1.81	0.070	.7386699	1.011962

For every additional maquiladora 2 years previously, there is a 0.63% increase in the number of foundings.

Coarsened Exact Matching with Linear Regression

founding	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
maquiladora_~t	8.096309	.3940324	20.55	0.000	7.323932	8.868686
border	-54.36328	12.79629	-4.25	0.000	-79.44639	-29.28017
ptotal	488.6033	14.66482	33.32	0.000	459.8575	517.3491
gini	403.8933	57.53789	7.02	0.000	291.1083	516.6783
rate_drug	-.6526117	.0943926	-6.91	0.000	-.8376389	-.4675845
lincome	100.2651	7.102737	14.12	0.000	86.34237	114.1878
homicidespc	-29957.2	12336.46	-2.43	0.015	-54138.97	-5775.437
_cons	-1126.042	73.57313	-15.31	0.000	-1270.259	-981.8245

The sample average treatment effect on the treated is 8.096.

The mean difference in new foundings between the untreated group (no maquiladoras) and treated group (>1 maquiladora) is 8.096.

Coarsened Exact Matching with Negative Binomial Regression

founding	IRR	Std. err.	z	P>|z|	[95% conf.	interval]
maquiladora_~t	1.067125	.0075175	9.22	0.000	1.052492	1.081961
border	.0327826	.0045745	-24.49	0.000	.0249382	.0430945
ptotal	1631.377	319.069	37.82	0.000	1111.921	2393.506
gini	360.2553	201.367	10.53	0.000	120.4553	1077.444
rate_drug	.9801361	.00089	-22.10	0.000	.9783932	.981882
lincome	2.734538	.1856341	14.82	0.000	2.393868	3.123689
homicidespc	0	0	-7.93	0.000	0	0
_cons	.0001	.0000711	-12.95	0.000	.0000248	.0004032
/lnalpha	1.154024	.0138197			1.126938	1.18111
alpha	3.170927	.0438213			3.086191	3.257989

The sample average treatment effect on the treated is 6.71%

The mean percentage difference in new foundings between the untreated group (no maquiladoras) and treated group (>1 maquiladora) is 6.71%.