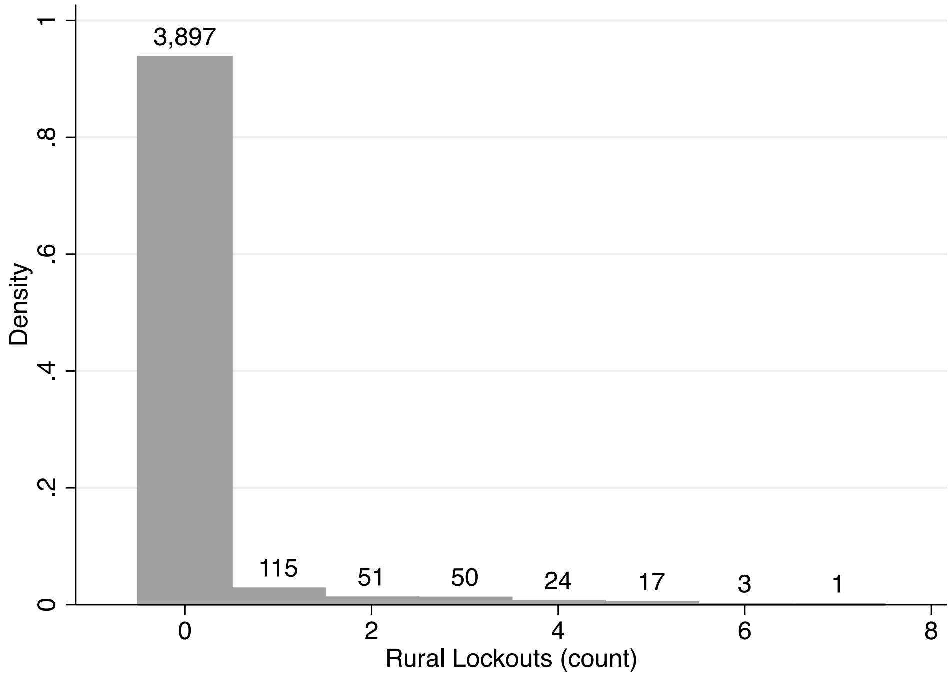
SUPPLEMENTARY APPENDIX

Protests of Abundance: Distributive Conflict over Agricultural Rents during the Commodities Boom in Argentina, 2003-2013

Contents

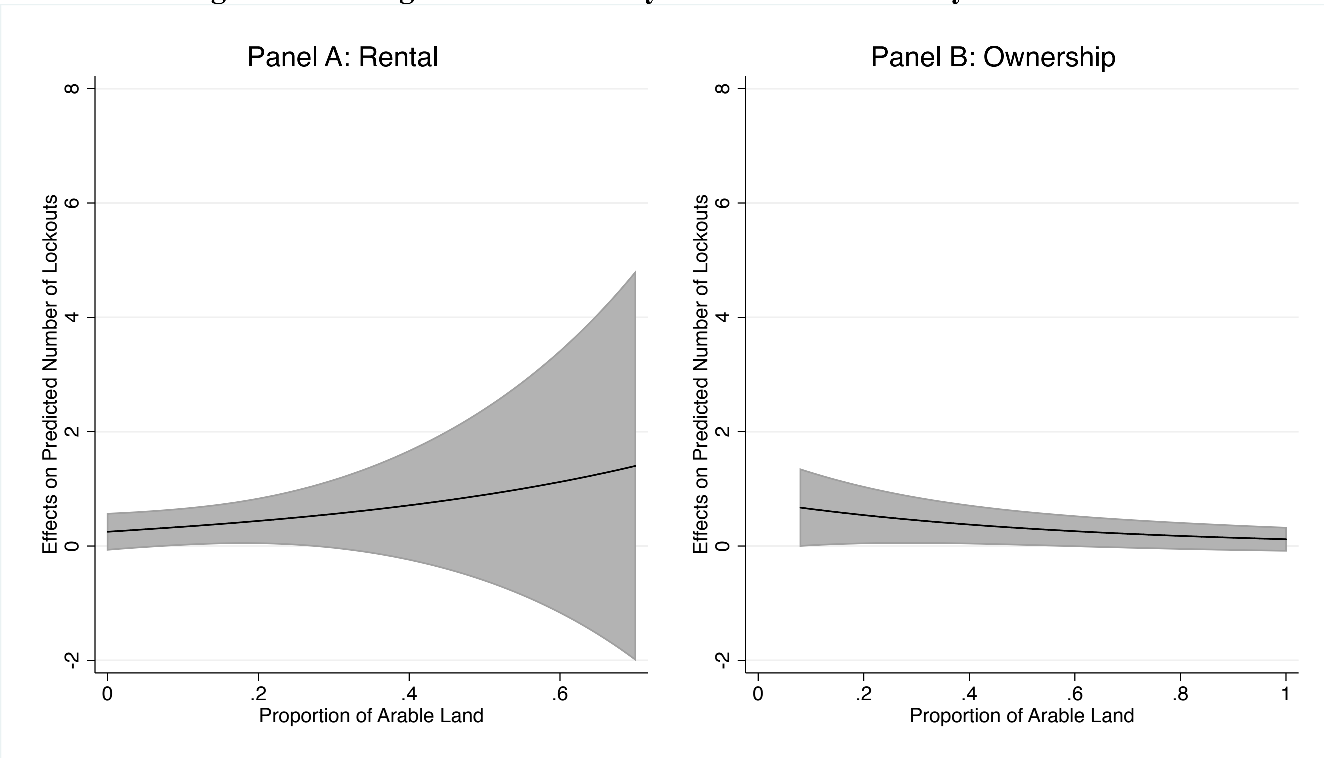
A. Additional Figures and Tables

Figure A1: Histogram of the Number of Rural Lockouts



Quantities at the top of the bins represent the frequency of each of the counts. The figure shows that 3,897 department-year observations (93.72% of the sample) did not experience a lockout in the studied period.

Figure A2: Marginal Effects of Soybean Tax Revenues by Land Tenure



Based on Models 1 and 2 (Table 3 from the paper). Confidence intervals are shown at the 95% level.

Table A1: Summary Statistics

Variables	N	Mean	Std. Dev.	Min	Max
Rural Lockouts (count)	4,158	0.138	0.631	0	7
Rural Lockouts (binary)	4,158	0.063	0.243	0	1
Rural Lockouts (farmers)	4,158	2,407	12,981	0	178,000
Population (log)	4,158	10.17	1.221	5.999	14.11
Farms (log)	4,158	6.201	0.986	0	8.436
Direct Costs – soybeans (log)	4,158	6.374	0.542	5.403	7.349
Direct Costs – maize (log)	4,158	6.933	0.461	6.296	7.840
Land Value (log)	4,158	8.408	1.644	3.421	11.60
Agricultural Product – w/out soybeans (log)	4,158	7.832	4.712	0	14.18
Agricultural Product – w/out maize (log)	4,158	6.278	4.952	0	13.93
Soybean Agro-Climatic Suitability	4,158	1.396	0.325	0	1.584
Soybean Export Tax (log)	4,158	6.031	0.689	4.744	6.880
Soybean Tax Revenues	4,158	6.942	1.521	0	8.235
Maize Tax Revenues	4,158	8.703	1.641	0	11.81
Rental	3,971	0.067	0.072	0	0.699
Ownership	4,103	0.621	0.216	0.077	1
CRA	4,158	0.489	0.500	0	1
CONINAGRO	4,158	0.315	0.464	0	1
FAA	4,158	0.336	0.472	0	1
Opposition Governor	4,158	0.166	0.373	0	1

The variable *Opposition Governor* captures if the provincial governor is an actual opponent of the president. We used Cherny et al. (2016) data base, which lists all the governors in 2003-2013 and identifies who supported or opposed the president in office.[1] *Opposition Governor* should depress the effect of *Soybean Tax Revenues* because governors that are not aligned with the president will be more responsive to local farmers' policy demands.

Table A2: Soybean Taxation, Opposition Governors, and Rural Lockouts

Soybean Tax Revenues	2.046***
	(0.551)
Opposition Governor	37.37***
	(5.458)
Soybean Tax Revenues × Opposition Governor	-5.346***
	(0.744)
Direct Costs (log) $_{t-1}$	-0.673
	(0.696)
Land Value (log) $_{t-1}$	-0.134
	(0.886)
Agricultural Product (log) $_{t-1}$	0.031*
	(0.016)
Farms (log)	0.605***
	(0.117)
Population (log)	0.232***
	(0.083)
Constant	-17.15***
	(1.454)
Pseudo R-squared	0.167
Log Likelihood	-1151
Observations	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed)

[1] This is done by examining electoral cues (for example, if the governor and the president were in the same ticket) but also important events in the provincial media, such as governors' public speeches or attendance at rallies organized by members of the national executive.

B. Robustness Checks

We conduct robustness checks and additional tests to evaluate how regression estimates behave when our main specifications are modified. We believe these exercises underline the robustness of the paper's main results. All the models we present below are unconditional fixed-effects negative binomial with province dummies and clustered standard errors by department (shown in parentheses in the tables). The dependent variable is the number of rural lockouts in a given department-year.

We begin by re-running our base models. We de-aggregate the two main components of *Soybean Tax Revenues* and construct an interaction term between them. We are concerned that rural lockouts might be driven by annual variations in global soybean prices or the national government's export tax policy rather than geographic asymmetries in soybean suitability, or vice versa. *Soybean Suitability* is the log of a department's agro-climatic attainable yield of soybeans, as operationalized in the paper.[2] *Soybean Export Tax* is the log of the international price of a metric ton of soybeans, weighted by the annual tax rate on soybean exports, measured in constant Argentine pesos. Thus, the term *Soybean Suitability* × *Soybean Export Tax* captures the effect of a raise in the national soybean export tax depending on how suitable a department is for cultivating soybeans. Table B1.1 shows no strong evidence in the constitutive terms. When a department's land is not apt for soybeans (i.e., *Soybean Suitability* equals zero), a government's export tax policy is not statistically significant. However, as *Soybean Suitability* becomes greater, *Soybean Export Tax* does have a positive and statistically significant effect on the number of lockouts, as the conditional marginal effect in Figure B1.1 illustrates.

Second, as noted in the paper, we are worried that our indicators for local rural organizations, in particular that of CRA, are proxying farm sizes instead of measuring farmers' incentives to engage in lockouts. Because members of CRA were predominantly mid-sized farmers, we estimate conditional effects using the proportion of a department's arable land that is occupied by farms between 100-500 hectares. According to the specialized literature and field interviews, this is the stratum characterizing CRA membership. Table B2.1 shows the estimates and Figure B2.1 plots the conditional marginal effect for various values of mid-sized farmland. The coefficient for the interaction is negative and statistically significant, implying that higher lockouts are not the outcome of production scales but rather of organizational incentives.

Third, we introduce dummies for each year instead of time trends. There might secular trends shaping both lockouts and soybean taxation—i.e., noncyclical features that exist over a long period of time. We decided to incorporate time trends and not year dummies due to statistical convergence issues. Tables B3.1-B3.3 report the estimates. Although lower in magnitude, the direction and significance of most of the results remain fairly unchanged.[3]

Fourth, we dropped the year 2008 and split the data set on a temporal basis. Figure 2 of the paper shows that much of the rural lockout activity (499) occurred in 2008, when farmer anti-government protests erupted. This could raise concerns about endogeneity with regard to our *Soybean Tax Revenues* variable, as stated on our paper. Tables B4.1-B4.3 show our main

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[2] FAO's GAEZ, at http://www.fao.org/nr/gaez/en/

[3] Though we do not show all the interaction plots, the replication files for this appendix contain the necessary code for graphing the conditional marginal effects (and predicted values) estimated throughout this section.

coefficients once we drop all the observations in 2008. The sign and statistical significance of some estimates, particularly those pertaining to rural organizations (Table B4.3), seem remarkably robust, although they are lower in magnitude and not significant for *Soybean Tax Revenues* when some of the conditional variables are set to 0. We find heterogeneous effects in the hypothesized direction for land tenure and rural organizations.

Fifth, because the national export tax rate stayed flat after the 2008 revolts, we explore and compare lockout activity in 2003-2008 (when the rate was raised four times) to that of 2009-2013 (remained flat at 35 percent). We should note that we were able to do this with only one of our base models. Severe convergence issues for the 2009-2013 sample emerged, as *Soybean Tax Revenues* loses statistical variance once the export tax rate becomes flat. We find no evidence of a strong effect in the 2009-2013 period, as expected.

Finally, we implement a placebo test. We address the following question: What if other primary activities are shaping rural lockouts? Because soybeans can be planted and harvested in zones where other crops are capable of growing too, it might be possible that *Soybean Tax Revenues* is "contaminated" by the potential fiscal revenues that, for example, corn or wheat are generating in a department. Consequently, we investigate the effect of export taxes on corn, or maize. Like soybeans, maize is a warm-season grain and relies on technological inputs alike. As we did with soybeans, we construct a *Maize Tax Revenues* explanatory variable using the international price of a metric ton of maize, weighted by the annual tax rate on maize exports,[4] and an average indicator of agro-climatically attainable yield for maize that. In this case, it is weighted by the share of produced maize that is actually exported in Argentina each year. We calculated the actual share of Argentina's exported maize using data from FAOSTAT, FAO's data base on agriculture and food.[5] It is important to note that, unlike soybeans, maize is not fully exported and is regulated by government trade policies since it is consumed domestically, like beef or wheat. Thus, and in contrast to soybeans, maize was not a source of profitable agricultural rents for Argentine farmers in the 2003-2013 period. Tables B6.1-B6.3 Figures B6.1-B6.2 show that the impact of *Maize Tax Revenues* on rural lockouts is indistinguishable from zero.

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[4] Argentine Oilseed Industry Chamber, http://www.ciaracec.com.ar/estadisticasNac.php

[5] http://www.fao.org/faostat/en/#home

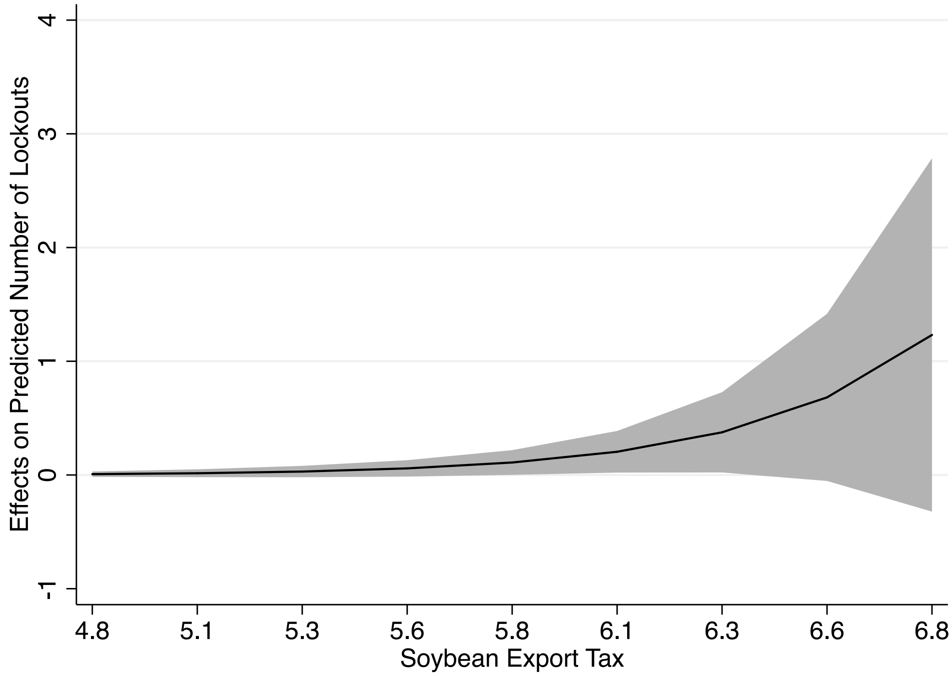
B1. Interaction between Soybean Suitability and Soybean Export Tax (base models)

Table B1.1: Soybean Taxation and Rural Lockouts

	(1)	(2)
Soybean Suitability (log)	-1.204	-2.817
	(4.022)	(4.186)
Soybean Export Tax (log)	0.920	0.911
	(0.999)	(0.982)
Soybean Suitability (log) × Soybean Export Tax (log)	0.424	0.733
	(0.650)	(0.693)
Direct Costs (log) $_{t-1}$		-0.760
		(0.589)
Land Value (log) $_{t-1}$		-0.057
		(0.097)
Agricultural Product (log) $_{t-1}$		0.028*
		(0.016)
Farms (log)	0.646***	0.589***
	(0.116)	(0.113)
Population (log)	0.242***	0.244**
	(0.078)	(0.083)
Constant	-15.34**	-10.28
	(6.142)	(6.911)
Time Trends	YES	YES
Pseudo R-squared	0.159	0.160
Log Likelihood	-1163	-1163
Observations	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Figure B1.1: Marginal Effects of Soybean Suitability by Soybean Export Tax



Based on Model 2 (Table B1.1). Confidence intervals are shown at the 95% level.

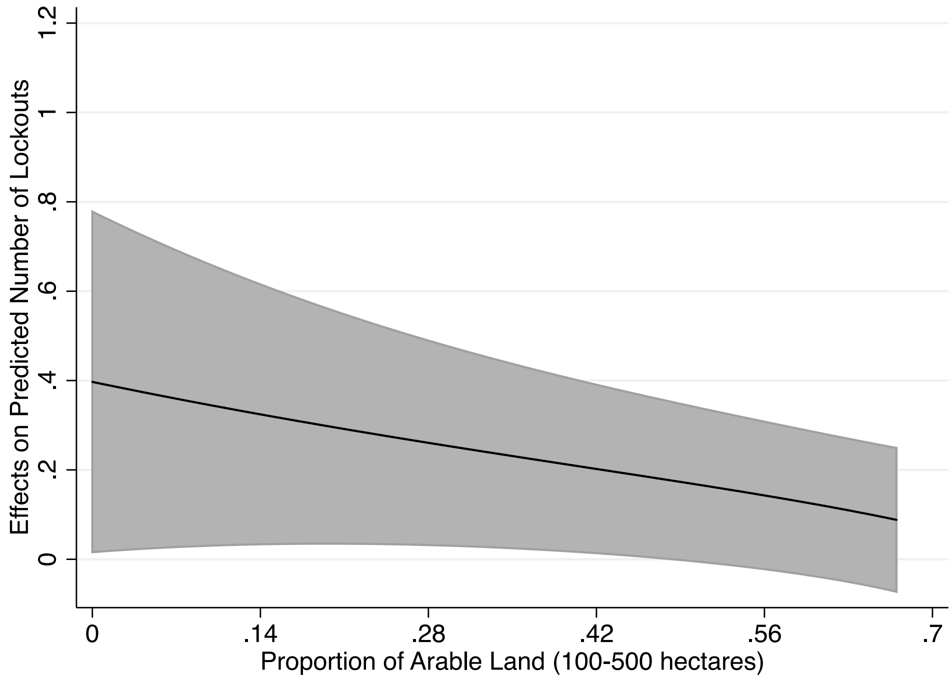
B2. Interaction between Soybean Tax Revenues and Mid-Sized Farms

Table B2.1: Soybean Taxation and Rural Lockouts

	(1)	(2)
Soybean Tax Revenues	1.720***	2.125***
	(0.161)	(0.505)
Mid-Sized Farms	17.721***	20.778***
	(2.846)	(4.650)
Soybean Tax Revenues × Mid-Sized Farms	-2.277***	-2.669***
	(0.376)	(0.616)
Direct Costs (log) $_{t-1}$		-0.498
		(0.596)
Land Value (log) $_{t-1}$		-0.144
		(0.901)
Agricultural Product (log) $_{t-1}$		0.028*
		(0.017)
Farms (log)	0.637***	0.579***
	(0.114)	(0.112)
Population (log)	0.227***	0.256***
	(0.376)	(0.081)
Constant	-20.20***	-18.92
	(1.587)	(1.460)
Time Trends	YES	YES
Pseudo R-squared	0.158	0.163
Log Likelihood	-1157	-1160
Observations	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Figure B2.1: Marginal Effects of Soybean Tax Revenues by Mid-Sized Farms



Based on Model 2 (Table B2.1). Confidence intervals are shown at the 95% level.

B3. Year Dummies

Table B3.1: Soybean Taxation and Rural Lockouts

	(1)	(2)
Soybean Tax Revenues	0.506*	0.363*
	(0.266)	(0.197)
Direct Costs (log) $_{t-1}$		0.004
		(0.548)
Land Value (log) $_{t-1}$		0.085
		(0.095)
Agricultural Product (log) $_{t-1}$		0.018
		(0.015)
Farms (log)	0.588***	0.563***
	(0.0983)	(0.103)
Population (log)	0.156**	0.125
	(0.0762)	(0.085)
Constant	-14.28***	-13.72***
	(2.470)	(4.209)
Year Dummies	YES	YES
Log Likelihood	-940	-939
Pseudo R-squared	0.320	0.321
Observations	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table B3.2: Soybean Taxation, Land Tenure, and Rural Lockouts

	(1)	(2)	(3)
Soybean Tax Revenues	0.276*	2.198***	1.229
	(0.163)	(0.776)	(0.772)
Rental	-66.016***		-53.034**
	(21.027)		(21.163)
Soybean Tax Revenues × Rental	8.412***		6.670**
	(2.734)		(2.734)
Ownership		14.574**	7.030
		(5.981)	(5.901)
Soybean Tax Revenues × Ownership		-1.973**	-0.996
		(0.793)	(0.779)
Direct Costs (log) $_{t-1}$	-0.224	-0.157	-0.202
	(0.554)	(0.598)	(0.588)
Land Value (log) $_{t-1}$	0.057	0.036	0.016
	(0.094)	(0.096)	(0.096)
Agricultural Product (log) $_{t-1}$	0.016	0.019	0.016
	(0.015)	(0.015)	(0.015)
Farms (log)	0.505***	0.565***	0.507***
	(0.114)	(0.108)	(0.115)
Population (log)	0.143*	0.126	0.144*
	(0.084)	(0.087)	(0.085)
Constant	-11.14***	-26.32***	-18.02***
	(4.233)	(6.420)	(6.397)
Year Dummies	YES	YES	YES
Pseudo R-squared	0.323	0.323	0.323
Log Likelihood	-926	-931	-924
Observations	3,971	4,103	3,971

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table B3.3: Soybean Taxation, Rural Organizations, and Rural Lockouts

	(1)	(2)	(3)	(4)
Soybean Tax Revenues	0.224*	0.374*	0.557*	0.459
	(0.127)	(0.211)	(0.331)	(0.302)
CRA	-12.889***			-14.186***
	(2.648)			(2.782)
Soybean Tax Revenues × CRA	1.924***			2.095***
	(0.357)			(0.375)
CONINAGRO		3.254		3.849*
		(2.230)		(2.095)
Soybean Tax Revenues × CONINAGRO		-0.425		-0.509*
		(0.292)		(0.273)
FAA			2.944	3.339*
			(2.012)	(1.908)
Soybean Tax Revenues × FAA			-0.392	-0.447*
			(0.266)	(0.251)
Direct Costs (log) $_{t-1}$	-0.773	0.058	-0.029	-0.868
	(0.532)	(0.579)	(0.548)	(0.561)
Land Value (log) $_{t-1}$	-0.030	0.093	0.091	-0.018
	(0.093)	(0.094)	(0.098)	(0.095)
Agricultural Product (log) $_{t-1}$	0.010	0.016	0.017	0.009
	(0.013)	(0.015)	(0.015)	(0.013)
Farms (log)	0.424***	0.554***	0.568***	0.437***
	(0.089)	(0.105)	(0.109)	(0.098)
Population (log)	0.139**	0.117	0.121	0.137**
	(0.061)	(0.083)	(0.084)	(0.061)
Constant	-7.677*	-14.051***	-15.002***	-8.938**
	(3.980)	(4.345)	(4.533)	(4.413)
Year Dummies	YES	YES	YES	YES
Pseudo R-squared	0.353	0.322	0.322	0.358
Log Likelihood	-894	-937	-937	-887
Observations	4,158	4,158	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

B4. Excluding 2008 from the Sample

Table B4.1: Soybean Taxation and Rural Lockouts

	(1)	(2)
Soybean Tax Revenues	0.713***	0.385*
	(0.146)	(0.222)
Direct Costs		0.464
		(0.310)
Land Value (log)		0.099
		(0.116)
Agricultural Product $_{t-1}$		0.024
		(0.023)
Farms (log) $_{t-1}$	0.618***	0.586***
	(0.127)	(0.131)
Population (log) $_{t-1}$	0.332***	0.297***
	(0.085)	(0.096)
Constant	-14.24***	-15.43***
	(1.487)	(1.517)
Time Trends	YES	YES
Pseudo R-squared	0.119	0.121
Log Likelihood	-767	-766
Observations	3,780	3,780

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table B4.2: Soybean Taxation, Land Tenure, and Rural Lockouts

	(1)	(2)	(3)
Soybean Tax Revenues	0.326	0.666	0.394
	(0.205)	(0.484)	(0.523)
Rental	-15.295		-16.587
	(11.337)		(12.442)
Soybean Tax Revenues × Rental	1.795		1.873
	(1.541)		(1.628)
Ownership		1.997	-0.319
		(3.580)	(3.870)
Soybean Tax Revenues × Ownership		-0.362	-0.088
		(0.498)	(0.527)
Direct Costs (log) $_{t-1}$	0.323	0.378	0.354
	(0.326)	(0.371)	(0.360)
Land Value (log) $_{t-1}$	0.095	0.076	0.058
	(0.120)	(0.118)	(0.121)
Agricultural Product (log) $_{t-1}$	0.020	0.022	0.017
	(0.022)	(0.022)	(0.022)
Farms (log)	0.523***	0.575***	0.513***
	(0.144)	(0.135)	(0.143)
Population (log)	0.317***	0.285***	0.305***
	(0.096)	(0.100)	(0.097)
Constant	-13.62***	-16.18***	-13.21***
	(1.915)	(2.303)	(3.024)
Time Trends	YES	YES	YES
Pseudo R-squared	0.115	0.119	0.116
Log Likelihood	-761	-762	-760
Observations	3,610	3,730	3,610

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table B4.3: Soybean Taxation, Rural Organizations, and Rural Lockouts

	(1)	(2)	(3)	(4)
Soybean Tax Revenues	0.141	0.391*	0.388*	0.176
	(0.141)	(0.237)	(0.234)	(0.154)
CRA	-5.159***			-5.916***
	(1.956)			(2.129)
Soybean Tax Revenues × CRA	0.852***			0.955***
	(0.266)			(0.294)
CONINAGRO		1.302		2.659
		(1.633)		(1.802)
Soybean Tax Revenues × CONINAGRO		-0.146		-0.344
		(0.216)		(0.238)
FAA			0.214	0.656
			(1.410)	(1.202)
Soybean Tax Revenues × FAA			-0.016	-0.084
			(0.189)	(0.160)
Direct Costs (log) $_{t-1}$	-0.183	0.547*	0.479	-0.143
	(0.356)	(0.302)	(0.309)	(0.354)
Land Value (log) $_{t-1}$	0.080	0.096	0.095	0.079
	(0.128)	(0.116)	(0.117)	(0.130)
Agricultural Product (log) $_{t-1}$	0.020	0.021	0.023	0.016
	(0.021)	(0.023)	(0.023)	(0.022)
Farms (log)	0.502***	0.552***	0.576***	0.472***
	(0.116)	(0.133)	(0.136)	(0.119)
Population (log)	0.272***	0.279***	0.289***	0.255***
	(0.078)	(0.095)	(0.091)	(0.077)
Constant	-9.542***	-15.61***	-15.38***	-9.728***
	(2.139)	(1.538)	(1.661)	(2.092)
Time Trends	YES	YES	YES	YES
Pseudo R-squared	0.129	0.121	0.120	0.130
Log Likelihood	-758	-765	-766	-757
Observations	3,780	3,780	3,780	3,780

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

B5. Splitting the Sample: 2003-2008 and 2009-2013 (base models)

Table B5.1: Soybean Taxation and Rural Lockouts

	2003-2008		2009-2013	
	(1)	(2)	(3)	(4)
Soybean Tax Revenues	2.495***	-	-0.441	0.012
	(0.262)		(0.528)	(0.268)
Direct Costs (log) $_{t-1}$		-		-6.817***
				(0.749)
Land Value (log) $_{t-1}$		-		0.110
				(0.214)
Agricultural Product (log) $_{t-1}$		-		0.030
				(0.334)
Farms (log)	0.612***	-	0.667***	0.470***
	(0.120)		(0.163)	(0.139)
Population (log)	0.174*	-	0.207*	0.145
	(0.093)		(0.109)	(0.128)
Constant	-24.55***	-	-4.013	38.63***
	(1.914)		(3.788)	(5.031)
Time Trends	YES	-	YES	YES
Pseudo R-squared	0.245	-	0.179	0.269
Log Likelihood	-651	-	-422	-376
Observations	2,268	-	1,890	1,890

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

B6. Placebo Tests: Taxing Maize Exports

Table B6.1: Maize Taxation and Rural Lockouts

	(1)	(2)
Maize Tax Revenues	0.030	-0.018
	(0.067)	(0.073)
Direct Costs (log) $_{t-1}$		0.566***
		(0.182)
Land Value (log) $_{t-1}$		0.245***
		(0.083)
Agricultural Product (log) $_{t-1}$		0.011
		(0.013)
Farms (log)	0.619***	0.653***
	(0.116)	(0.122)
Population (log)	0.265***	0.174*
	(0.076)	(0.090)
Constant	-7.683***	-12.88***
	(0.809)	(1.320)
Time Trends	YES	YES
Pseudo R-squared	0.131	0.136
Log Likelihood	-1200	-1194
Observations	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table B6.2: Maize Taxation, Land Tenure, and Rural Lockouts

	(1)	(2)	(3)
Maize Tax Revenues	-0.180*	0.366	0.012
	(0.109)	(0.238)	(0.285)
Rental	-31.105**		-28.248**
	(13.684)		(13.986)
Maize Tax Revenues × Rental	3.191**		2.863*
	(1.505)		(1.522)
Ownership	0.372	5.081*	1.910
	(0.233)	(2.990)	(3.194)
Maize Tax Revenues × Ownership		-0.579*	-0.251
		(0.331)	(0.353)
Direct Costs (log) $_{t-1}$	0.372	0.413*	0.334
	(0.233)	(0.219)	(0.238)
Land Value (log) $_{t-1}$	0.294***	0.293***	0.297***
	(0.092)	(0.096)	(0.099)
Agricultural Product (log) $_{t-1}$	0.010	0.011	0.009
	(0.013)	(0.013)	(0.012)
Farms (log)	0.434***	0.566***	0.406***
	(0.146)	(0.138)	(0.148)
Population (log)	0.224**	0.172*	0.220**
	(0.088)	(0.094)	(0.089)
Constant	-9.438***	-15.09***	-10.53***
	(1.999)	(1.974)	(2.852)
Time Trends	YES	YES	YES
Pseudo R-squared	0.132	0.135	0.133
Log Likelihood	-1185	-1189	-1185
Observations	3,971	4,103	3,971

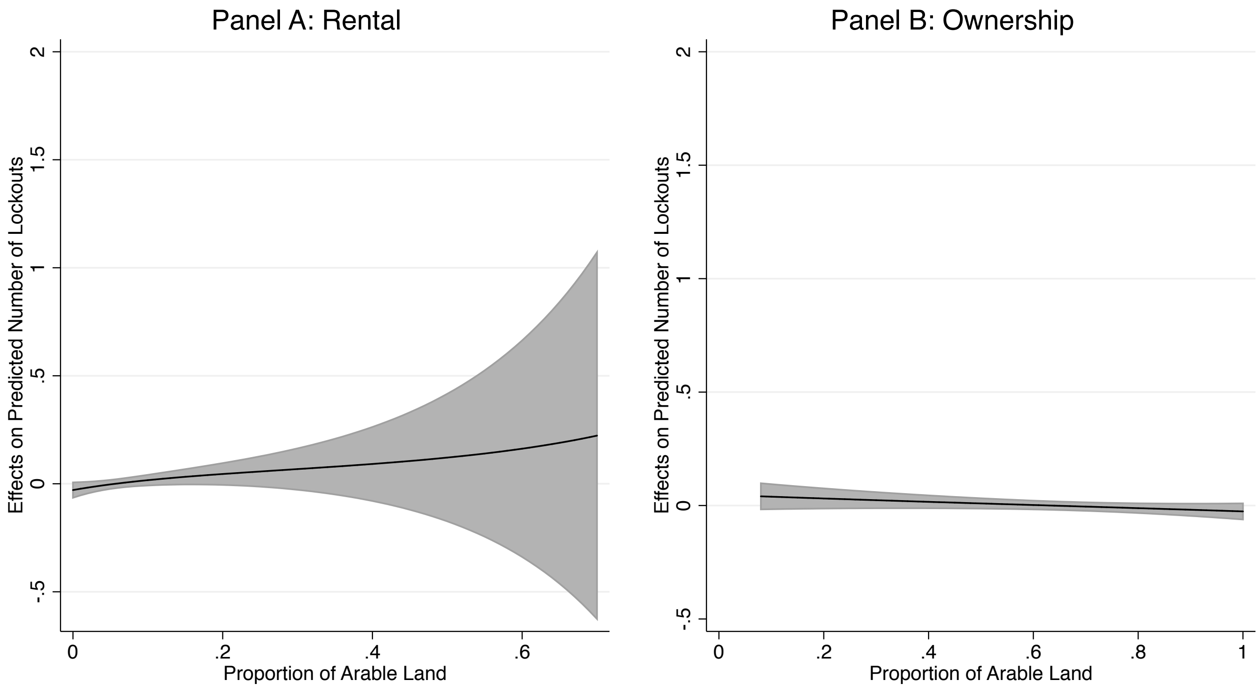
*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table B6.3: Maize Taxation, Rural Organizations, and Rural Lockouts

	(1)	(2)	(3)	(4)
Maize Tax Revenues	-0.055	0.014	0.028	-0.029
	(0.097)	(0.082)	(0.078)	(0.095)
CRA	1.742			0.897
	(1.171)			(1.282)
Maize Tax Revenues × CRA	-0.051			0.047
	(0.125)			(0.139)
CONINAGRO		1.781		1.352
		(1.691)		(1.483)
Maize Tax Revenues × CONINAGRO		-0.190		-0.151
		(0.182)		(0.161)
FAA			1.775	1.713
			(1.353)	(1.305)
Maize Tax Revenues × FAA			-0.194	-0.192
			(0.144)	(0.141)
Direct Costs (log) $_{t-1}$	0.665***	0.612***	0.615***	0.693***
	(0.201)	(0.189)	(0.186)	(0.201)
Land Value (log) $_{t-1}$	0.188**	0.230**	0.233***	0.178*
	(0.091)	(0.087)	(0.084)	(0.091)
Agricultural Product (log) $_{t-1}$	0.010	0.011	0.012	0.012
	(0.012)	(0.012)	(0.012)	(0.012)
Farms (log)	0.586***	0.659***	0.661***	0.598***
	(0.110)	(0.121)	(0.126)	(0.112)
Population (log)	0.122*	0.172*	0.169**	0.120*
	(0.069)	(0.091)	(0.085)	(0.070)
Constant	-13.00***	-13.39***	-13.54***	-13.41***
	(1.532)	(1.393)	(1.361)	(1.566)
Time Trends	YES	YES	YES	YES
Pseudo R-squared	0.145	0.136	0.136	0.146
Log Likelihood	-1182	-1194	-1194	-1181
Observations	4,158	4,158	4,158	4,158

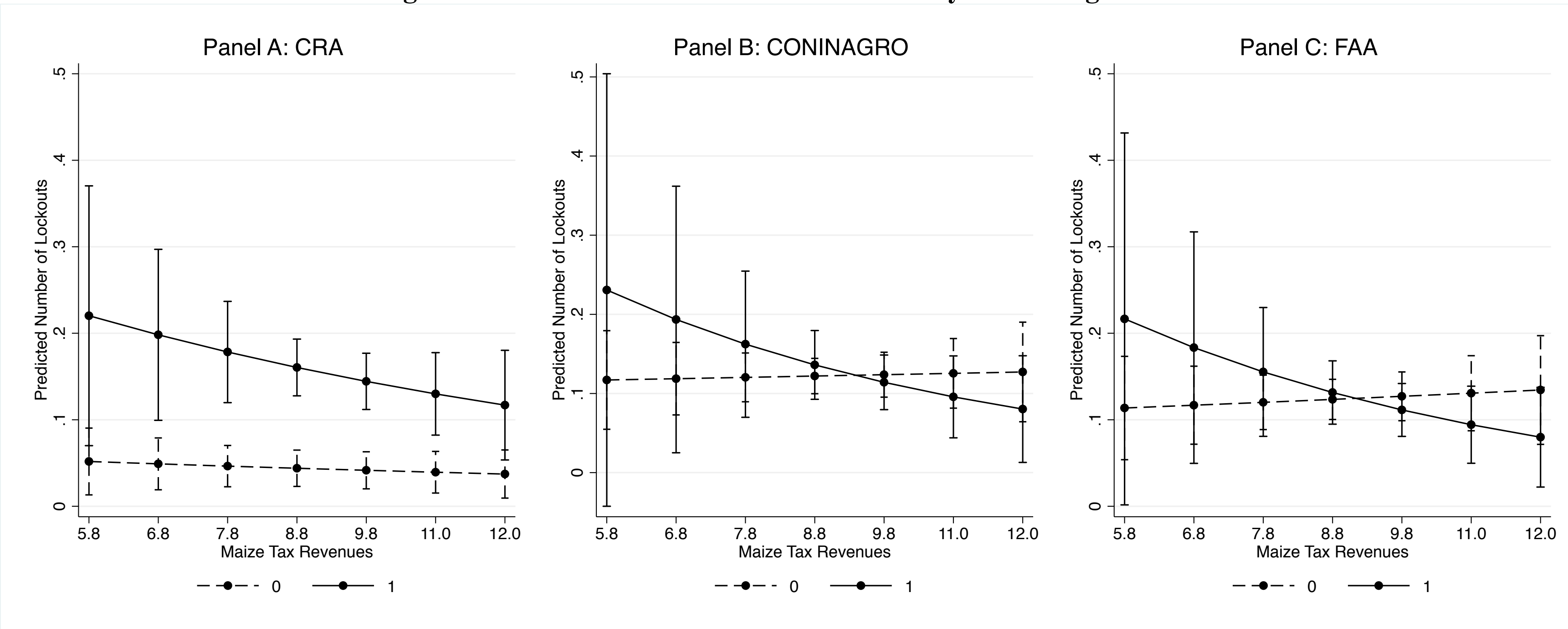
*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Figure B6.1: Marginal Effects of Maize Tax Revenues by Land Tenure



Based on Models 1 and 2 (Table B6.2). Confidence intervals are shown at the 95% level.

Figure B6.2: Predicted Number of Lockouts by Rural Organizations



Maize Tax Revenues is plotted from its mean to its maximum value. Based on Models 1, 2, and 3 (Table B6.3). Confidence intervals are shown at the 95% level.

C. Sensitivity Analysis

There are three estimators for count data in a panel structure that are reasonable alternatives to the unconditional fixed-effects negative binomial. All of them adjust the likelihood-based function to account for the extra correlation, and can be organized in two classes (e.g., Hilbe, 2007). The first one is the population-average or generalized estimating equation (GEE), which essentially models the average response of units sharing the same predictors across all panels. The second class of estimators refers to those commonly known as unit-specific estimators, like fixed effects and random effects. Fixed-effects models can be estimated in a conditional (the estimation is conditional on the value of a sufficient statistic for one or more parameters) or unconditional (all parameters are estimated) way. An alternative to our estimation strategy would be a conditional fixed-effects estimator. Finally, random-effects models assume that constants and predictors are uncorrelated.

Additionally, we cope with abundant zeroes in our dependent variable. Figure A1 shows that 93.72 percent of our observations (3,897) have zero counts. We dealt with that tissue in Table 2 (Models 1 and 2) of the paper by excluding those departments that never experienced a rural lockout in the sample period. An alternative would be to implement a zero-inflated estimator. A zero-inflated negative binomial (ZINB) relies on two separate estimation procedures (e.g., Greene 1994; Lambert 1992; Long 1997). A standard negative binomial model for predicting the number of event occurrences and a binary response model, such as a probit or logit, to predict zero counts. In other words, a ZINB framework supposes that there are two sorts of units in the data. One group comes from a discrete probability distribution. Zeros in this group are true zeros—they could have been positive counts but, for some reason, they were not.[6] A second group has excess or structural zeroes, which means that these units have zero probability of a nonnegative count.

Tables C1.1-C3.1 present the results for these alternative techniques.[7] Standard errors are in parentheses. The dependent variable in all the estimations is the number of lockouts per department-year. The GEE negative binomial was executed using an autoregressive correlation structure of order one (AR1)—appropriate for accommodating temporal-dependent processes. We bootstrapped standard errors with 100 replications in the GEE negative binomial. The conditional fixed-effects models were estimated at the department level.[8] We bootstrapped standard errors for the conditional procedure too, this time performing 50 replications.[9] As described in the paper, this

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[6] It could be the case that some departments may never experience a lockout because local farmers lack the motivation for engaging in that type of protests. Farmers might be reluctant to participate in a lockout because their household income depends on commercialization activities, fear that the government may take reprisals against, or simply do not have the political skills to organize one.
[7] Similarly, we provide the code for building the interaction plots in the replication files.
[8] We did not implement an unconditional variant with departmental dummies. As we anticipated in the paper, the procedure is computationally taxing since the number of departments is relatively large and does not achieve convergence in most of our models. More worryingly, average predicted values could not be estimated with the utilized software. These models are also prone to incidental parameter bias, an issue that does not seem to be irrelevant because the number of repeated observations per department through the time period is small.
[9] We had to set the number of replications to 50 in these models due to software's inability to reach 100. However, it is argued that 50-200 replications are adequate (Mooney & Duval, 1993).

method is problematic for our data so its results must be taken with caution. As it relies on within-department variation, it dropped 228 departments (2,508 observations, or 60.32 percent of the sample) because of all zero outcomes.

Lastly, the ZINB models were estimated with clustered standard errors by department. We used the same predictors for both the negative binomial and logit regressions. However, as demonstrated elsewhere (e.g., Czado et al., 2007; Famoye & Singh, 2006; Lambert, 1992), the iterative process of maximum likelihood to estimate the parameters of ZINB models is highly sensitive to convergence failures. As a result, we were able to re-estimate only the base models using this approach. We are also skeptical about this procedure for three reasons. First, we are unaware of a ZINB implementation for panel data in the specialized literature. Second, applying the same set of variables to both estimations means that the data generating process is the same, which appears to be inconsistent with the rationale for using a zero-inflated estimator—see Li (2005) for this discussion.[10] Third, as Allison (2012) suggests, the fit of a conventional negative binomial is as good as that of a ZINB. The difference in fit is usually trivial because the unobserved heterogeneity that can generate over-dispersion can also generate excess zeroes (Cameron & Trivedi, 2013; Long, 1997).

Overall, our estimates seem to be fairly robust to changes in the estimator. The coefficients for *Soybean Tax Revenues* have similar magnitudes. They are also statistically significant at the conventional levels. Even the conditional fixed-effects estimator, which produces a loss of efficiency and larger standard errors, confirms the high significance of *Soybean Tax Revenues*. The coefficients for the interaction terms tend to confirm the direction and significance of our conditional hypotheses by land tenure and rural organization.

[10] We would need to collect data on individual motivations to analyze what determines a farmer's decision to go on a lockout, something implausible at the aggregate level.

C1. Generalized Estimating Equations Negative Binomial

Table C1.1: Soybean Taxation and Rural Lockouts

	GEE-NB (1)	GEE-NB (2)
Soybean Tax Revenues	1.220***	2.779***
	(0.109)	(0.437)
Direct Costs (log) $_{t-1}$		-2.853***
		(0.536)
Land Value (log) $_{t-1}$		0.342***
		(0.093)
Agricultural Product (log) $_{t-1}$		0.050
		(0.031)
Farms (log)	0.051	0.030
	(0.080)	(0.101)
Population (log)	-0.009	-0.159**
	(0.064)	(0.087)
Constant	-11.30***	-6.271***
	(1.067)	(1.223)
Standard Errors	BS	BS
Fixed Effects	NO	NO
Time Trends	NO	NO
Wald χ^2	119.5	125.6
Observations	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table C1.2: Soybean Taxation, Land Tenure, and Rural Lockouts

	GEE-NB (1)	GEE-NB (2)	GEE-NB (3)
Soybean Tax Revenues	2.547***	3.190***	2.790***
	(0.521)	(0.555)	(0.601)
Rental	-17.392		-16.735
	(11.755)		(11.511)
Soybean Tax Revenues × Rental	2.725*		2.441**
	(1.584)		(1.142)
Ownership		4.757	2.516
		(4.940)	(4.888)
Soybean Tax Revenues × Ownership		-0.912	-0.586
		(0.654)	(0.650)
Direct Costs (log) $_{t-1}$	-2.774***	-2.535***	-2.484***
	(0.573)	(0.591)	(0.562)
Land Value (log) $_{t-1}$	0.293***	0.166*	0.149
	(0.102)	(0.086)	(0.098)
Agricultural Product (log) $_{t-1}$	0.045	0.036	0.034
	(0.031)	(0.034)	(0.034)
Farms (log)	0.012	0.053	0.027
	(0.107)	(0.110)	(0.125)
Population (log)	-0.159**	-0.201**	-0.188**
	(0.069)	(0.088)	(0.095)
Constant	-4.668***	-8.288***	-5.634**
	(1.819)	(2.908)	(2.839)
Standard Errors	BS	BS	BS
Fixed Effects	NO	NO	NO
Time Trends	NO	NO	NO
Wald χ^2	128.2	162.7	164
Observations	3,971	4,103	3,971

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table C1.3: Soybean Taxation, Rural Organizations, and Rural Lockouts

	GEE-NB (1)	GEE-NB (2)	GEE-NB (3)	GEE-NB (4)
Soybean Tax Revenues	0.845**	3.051***	3.067***	1.223**
	(0.364)	(0.529)	(0.468)	(0.550)
CRA	-11.225***			-12.909***
	(2.022)			(2.637)
Soybean Tax Revenues × CRA	1.837***			2.057***
	(0.288)			(0.368)
CONINAGRO		3.862**		3.546**
		(1.715)		(1.556)
Soybean Tax Revenues × CONINAGRO		-0.524**		-0.488**
		(0.226)		(0.207)
FAA			3.866**	4.250**
			(1.839)	(1.772)
Soybean Tax Revenues × FAA			-0.491**	-0.549**
			(0.240)	(0.237)
Direct Costs (log) $_{t-1}$	-1.974***	-2.984***	-2.940***	-2.138***
	(0.379)	(0.576)	(0.536)	(0.489)
Land Value (log) $_{t-1}$	0.032	0.355***	0.334***	0.035
	(0.100)	(0.096)	(0.101)	(0.096)
Agricultural Product (log) $_{t-1}$	0.032	0.049	0.046	0.031
	(0.029)	(0.034)	(0.037)	(0.025)
Farms (log)	-0.055	0.053	0.018	-0.026
	(0.098)	(0.105)	(0.110)	(0.105)
Population (log)	-0.152**	-0.151*	-0.171**	-0.144*
	(0.075)	(0.086)	(0.078)	(0.083)
Constant	3.828**	-7.774***	-7.638***	1.787
	(1.763)	(1.643)	(1.678)	(2.321)
Standard Errors	BS	BS	BS	BS
Fixed Effects	NO	NO	NO	NO
Time Trends	NO	NO	NO	NO
Wald χ^2	344	146	133.4	320.8
Observations	4,158	4,158	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

C.2 Conditional Fixed-Effects Negative Binomial (department-level)

Table C2.1: Soybean Taxation and Rural Lockouts

	FE-NB (1)	FE-NB (2)
Soybean Tax Revenues	0.704***	2.710***
	(0.076)	(0.490)
Direct Costs (log) $_{t-1}$		-1.089***
		(0.394)
Land Value (log) $_{t-1}$		-1.063***
		(0.354)
Agricultural Product (log) $_{t-1}$		0.032
		(0.035)
Farms (log)	0.061	-0.240
	(0.150)	(0.315)
Population (log)	0.260**	0.546***
	(0.125)	(0.245)
Constant	-10.53***	-9.590***
	(1.457)	(2.205)
Standard Errors	BS	BS
Fixed Effects	DEPT.	DEPT.
Time Trends	YES	YES
Wald χ^2	1.470e+09	97005
Log Likelihood	-734	-709
Observations	1,650	1,650

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table C2.2: Soybean Taxation, Land Tenure, and Rural Lockouts

	FE-NB (1)	FE-NB (2)	FE-NB (3)
Soybean Tax Revenues	2.462***	3.060***	2.430***
	(0.600)	(0.550)	(0.863)
Rental	-30.797		-38.797**
	(19.728)		(15.976)
Soybean Tax Revenues × Rental	4.148		4.837**
	(2.639)		(1.961)
Ownership		-2.421	-6.262
		(6.452)	(5.250)
Soybean Tax Revenues × Ownership		-0.279	0.211
		(0.890)	(0.813)
Direct Costs (log) $_{t-1}$	-1.180***	-1.027*	-1.078*
	(0.452)	(0.598)	(0.559)
Land Value (log) $_{t-1}$	-1.110*	-1.283***	-1.288***
	(0.628)	(0.338)	0.453
Agricultural Product (log) $_{t-1}$	0.037	0.016	0.016
	(0.070)	(0.052)	(0.072)
Farms (log)	-0.263	-0.358	-0.374
	(0.317)	(0.258)	(0.337)
Population (log)	0.561***	0.521***	0.532**
	(0.162)	(0.128)	(0.215)
Constant	-6.764**	-7.163**	-1.749
	(3.148)	(3.652)	(4.165)
Standard Errors	BS	BS	BS
Fixed Effects	DEPT.	DEPT.	DEPT.
Time Trends	YES	YES	YES
Wald χ^2	14035	148521	16958
Log Likelihood	-705	-701	-699
Observations	1,639	1,639	1,639

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table C2.3: Soybean Taxation, Rural Organizations, and Rural Lockouts

	FE-NB (1)	FE-NB (2)	FE-NB (3)	FE-NB (4)
Soybean Tax Revenues	1.722***	2.941***	2.846***	2.046***
	(0.557)	(0.624)	(0.485)	(0.699)
CRA	-8.787***			-9.512***
	(2.922)			(3.004)
Soybean Tax Revenues × CRA	1.271***			1.393***
	(0.401)			(0.430)
CONINAGRO		3.364**		3.991***
		(1.441)		(1.535)
Soybean Tax Revenues × CONINAGRO		-0.421**		-0.496***
		(0.171)		(0.188)
FAA			1.695*	1.659
			(0.995)	(1.265)
Soybean Tax Revenues × FAA			-0.149	-0.139
			(0.128)	(0.150)
Direct Costs (log) $_{t-1}$	-1.274**	-1.193**	-1.039**	-1.335**
	(0.519)	(0.482)	(0.461)	(0.614)
Land Value (log) $_{t-1}$	-1.111*	-1.046*	-1.145***	-1.215**
	(0.601)	(0.547)	(0.417)	(0.483)
Agricultural Product (log) $_{t-1}$	0.036	0.025	0.020	0.014
	(0.045)	(0.033)	(0.071)	(0.060)
Farms (log)	-0.264	-0.299	-0.372	-0.474*
	(0.487)	(0.430)	(0.394)	(0.244)
Population (log)	0.541**	0.493**	0.505**	0.446**
	(0.256)	(0.210)	(0.225)	(0.195)
Constant	-1.083	-9.905***	-9.036***	-0.171
	(3.752)	(3.126)	(2.356)	(2.828)
Standard Errors	BS	BS	BS	BS
Fixed Effects	DEPT.	DEPT.	DEPT.	DEPT.
Time Trends	YES	YES	YES	YES
Wald χ^2	12483	15969	33404	5.859e+06
Log Likelihood	-704	-708	-708	-700
Observations	1,650	1,650	1,650	1,650

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

C.3 Random-Effects Negative Binomial

Table C3.1: Soybean Taxation and Rural Lockouts

	RE-NB (1)	RE-NB (2)
Soybean Tax Revenues	0.564***	1.414***
	(0.094)	(0.269)
Direct Costs (log) $_{t-1}$		-1.631***
		(0.328)
Land Value (log) $_{t-1}$		0.326***
		(0.077)
Agricultural Product (log) $_{t-1}$		0.058***
		(0.025)
Farms (log)	0.048***	-0.015
	(0.082)	(0.108)
Population (log)	0.139**	0.049
	(0.063)	(0.064)
Constant	-8.414***	-5.671***
	(0.980)	(1.040)
Standard Errors	ML	ML
Fixed Effects	NO	NO
Time Trends	NO	NO
Wald χ^2	49	98
Log Likelihood	-1347	-1310
Observations	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table C3.2: Soybean Taxation, Land Tenure, and Rural Lockouts

	RE-NB	RE-NB	RE-NB
	(1)	(2)	(3)
Soybean Tax Revenues	1.437***	1.812***	1.462***
	(0.515)	(0.392)	(0.489)
Rental	-45.561**		-14.61
	(18.157)		(14.43)
Soybean Tax Revenues × Rental	6.793***		2.130
	(2.553)		(1.906)
Ownership		4.079	1.892
		(3.830)	(4.357)
Soybean Tax Revenues × Ownership		-0.767	-1.892
		(0.515)	(4.357)
Direct Costs (log) $_{t-1}$	-1.967***	-1.471***	-1.443***
	(0.506)	(0.330)	(0.331)
Land Value (log) $_{t-1}$	0.375***	0.203**	0.187
	(0.103)	(0.082)	(0.081)
Agricultural Product (log) $_{t-1}$	0.041*	0.044**	0.040*
	(0.025)	(0.021)	(0.021)
Farms (log)	0.073	0.010	-0.016
	(0.112)	(0.082)	(0.087)
Population (log)	-0.055	-0.100	-0.091
	(0.080)	(0.065)	(0.065)
Constant	-3.3955**	-7.166***	-4.642
	(1.639)	(2.264)	(3.190)
Standard Errors	ML	ML	ML
Fixed Effects	NO	NO	NO
Time Trends	NO	NO	NO
Wald χ^2	153	130	127
Log Likelihood	-1284	-1293	-1270
Observations	3,971	4,103	3,971

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Table C3.3: Soybean Taxation, Rural Organizations, and Rural Lockouts

	RE-NB (1)	RE-NB (2)	RE-NB (3)	RE-NB (4)
Soybean Tax Revenues	0.443	1.614***	2.116***	0.643**
	(0.270)	(0.462)	(0.485)	(0.318)
CRA	-7.328***			-8.810***
	(1.870)			(1.990)
Soybean Tax Revenues × CRA	1.259***			1.458***
	(0.263)			(0.280)
CONINAGRO		3.336**		3.387**
		(1.570)		(1.540)
Soybean Tax Revenues × CONINAGRO		-0.444**		-0.461**
		(0.210)		(0.206)
FAA			2.110	2.214
			(2.055)	(1.538)
Soybean Tax Revenues × FAA			-0.257	-0.284
			(0.275)	(0.205)
Direct Costs (log) $_{t-1}$	-1.507***	-1.668***	-2.104***	-1.563***
	(0.314)	(0.335)	(0.502)	(0.330)
Land Value (log) $_{t-1}$	0.122	-0.334***	0.413***	0.116
	(0.078)	(0.077)	(0.097)	(0.080)
Agricultural Product (log) $_{t-1}$	0.030	0.055***	0.040	0.028
	(0.020)	(0.021)	(0.025)	(0.020)
Farms (log)	-0.083	-0.011	0.096	-0.075
	(0.082)	(0.083)	(0.101)	(0.087)
Population (log)	-0.064	-0.054	-0.099	-0.065
	(0.062)	(0.065)	(0.079)	(0.065)
Constant	1.888	-6.957***	-7.827***	0.776
	(1.851)	(1.263)	(1.342)	(1.992)
Standard Errors	ML	ML	ML	ML
Fixed Effects	NO	NO	NO	NO
Time Trends	NO	NO	NO	NO
Wald χ^2	177	97	114	178
Log Likelihood	-1246	-1307	-1302	-1242

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

C.4 Zero-Inflated Negative Binomial

Table C4.1: Soybean Taxation and Rural Lockouts

	Lockouts Count	Zero Outcomes	Lockouts Count	Zero Outcomes
	NB	Logit	NB	Logit
	(1)	(2)	(3)	(4)
Soybean Tax Revenues	1.470***	0.350	1.841***	-0.149
	(0.280)	(0.252)	(0.363)	(0.402)
Direct Costs (log) $_{t-1}$			-0.667	1.176**
			(0.732)	(0.585)
Land Value (log) $_{t-1}$			-0.048	-0.399***
			(0.091)	(0.116)
Agricultural Product (log) $_{t-1}$			0.005	-0.056*
			(0.015)	(0.029)
Farms (log)	0.162	0.040	0.174	0.106
	(0.141)	(0.117)	(0.124)	(0.121)
Population (log)	-0.104	-0.181**	-0.093	-0.008
	(0.087)	(0.073)	(0.078)	(0.087)
Constant	-10.60***	1.114	-8.823**	-0.868
	(2.486)	(2.310)	(4.099)	(3.768)
Standard Errors	CL	CL	CL	CL
Fixed Effects	NO	NO	NO	NO
Time Trends	NO	NO	NO	NO
Pseudo R^2	0.032	0.032	0.034	0.034
Log Likelihood	-1292	-1292	-1255	-1255
Observations	4,158	4,158	4,158	4,158

*** $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

D. Qualitative Appendix

We provide two types of qualitative data to support for our findings. These data, more relevantly, shed light on the causal pathways of our theory on agricultural rents and rural lockouts. First, we introduce materials from a comprehensive ethnographic case study that Millán (2010), an Argentine sociologist, conducted in a rural town of Santa Fe between 2007 and 2009. This scholar explores, and finds, similar mechanisms to the ones outlined in our argument. In his work, the mechanisms were elaborated to explain changes in the identity of farmers. We transcribe verbatim excerpts as well as quotations from his study.

Second, we incorporate the hyperlinked citations of the paper—that is, textual evidence from semi-structured interviews we conducted in the field between 2014 and 2016.[11] We present them following the active citations standard that Moravscik (2012, p. 35) proposes, which ensures "the use of rigorous, annotated citations hyperlinked to the sources themselves." Entries contain a copy of the full citation; a larger excerpt or transcript from the source, where the citation is embedded; and, when necessary, annotations explaining how the source supports a theoretical claim, informing contextual details of the interview (for example, if it was conducted during an annual assembly of a farmers), or summarizing documents, such as legislative bills, that might be relevant to our argument. We believe these interviews elucidate some relevant aspects of the context in which the causal processes of our theory occur (Falleti & Lynch, 2009). They illuminate the temporal (e.g., from an era of economic stagnation in the 1990s to the commodities boom of the 2000s) and spatial (e.g., regulatory, fiscal, and organizational decisions made both at the federal and local level) settings leading to events of rural lockouts in Argentina in 2003-2013. We list the hyperlinks in numerical order, as they appear in the paper.

D.1 Evidence from a Case Study

Bigand is a rural township located in the south of the province of Santa Fe, at the core of the Argentina's soybean-producing region. It is seventy kilometers away from Rosario, where the chief port for exporting soybean operates. It is connected to it by a railroad only used for cargo. The town is named after the landlord who founded it and who established a system of sharecropping to sustain agriculture across his lands. The family of the landlord always resided in Buenos Aires. Immigration from Italy, Spain, France, Serbia, and Croatia supplied the labor and the some of the first inhabitants who populated the town. Sharecropping contracts were inherited within the family. Many turned into property owners during the presidency of Juan Domingo Perón.

According to the 2001 census, 5,062 inhabitants populate the town, of which only 644 are rural and the rest are urban. One third of the families is involved in agriculture-related activities. These include farmers who work in lands surrounding Bigand and other locations as well as suppliers in charge of planting, harvesting, machinery, and services, who also work in other areas and provinces.

The town also depends on indirect activities related to agriculture, as a local commonplace expression illustrates: "everything depends on the countryside here." The contrast between the

[11] The case study as well as the interviews were conducted in Spanish and translated by the authors.

economic distress of the 1990s and the impact of the commodities boom in the 2000s, which we mention in the paper, emerged in the interviews cited in Millán's (2010) case study:

> *"I say that 'the countryside should be well so that we're all well'. Because if they stop, we're affected directly or indirectly because the sales of machines come down, the sales of supplies decline, we all sell less and it affects us."* [Shop clerk, August 2009, 133-4]

> *"…the producers…that sold their land, that experience economic distress…try to muddle to make it through the crisis, but there sure was an exodus to the city, especially for their children because if the father had to sell the land, o even if by miracle he retained the land, the future of his children to continue in the agricultural activity was closing…"* [Interview with a former head of the local government back in the 1990s, November 2007, 134]

> *"Here, when the countryside is producing, everything is moving. When there is work in the countryside, the longshoremen also work. The union calls all the men to work as longshoremen. Meanwhile other union benefits because transportation workers are hired to bring seeds to the countryside."* [Local farmer, August 2009, 134]

> *"Yes, it's the volatility of the economy. The devaluation of the dollar has its more positive effect on the export sector because they sell in dollars and produce with a domestic cost. With the devaluation these [agricultural] sectors recovered all the ground they had lost with the crisis and are now growing."* [Head of the local government, November 2007, 144].

The town has three companies with large grain storage facilities as well as sale of inputs, supplies, seeds, and agrochemicals. One is privately owned and two are cooperatives. The largest cooperative is part of Federated Argentine Farmers (AFA), associated to the Agrarian Federation of Argentina (FAA). The AFA has been traditionally important in organizing local sharecroppers whose descendants became small- and medium-size landholders. The second cooperative is connected to the Association of Argentine Cooperatives (ACA), which itself belongs to the Confederation of Agrarian Cooperatives (CONINAGRO). There is no mention of a local farmers' association affiliated to a regional member of the Rural Confederations of Argentina (CRA).

The cost of lockouts that we refer to in the paper are brought up by Millán (2010), who writes:

> *"When there is a commercialization lockout, the first groups affected by the lack of employment, and thus of income, are the employees and the service providers in the agricultural sector, such as transportation workers, longshoremen, pest control workers…The retail sector, the transportation, and the mechanical industry in the town were also affected by the decline in the circulating of money flows at the local level."* (144).

> *"In terms of political mobilization, the participation of local producers in the 2008 conflict was limited. Those who mobilized and protest, joined the FAA and the AFA (Federated Argentine Farmers, which had the largest grain storage facility). They joined road*

blockades, and on May 15 and there was a demonstration on rural vehicles to the head of the local government." (145).

How the costs of lockouts are distributed may explain that the head of the local government, although aligned with President Kirchner, supported the rural demands in 2008. There is also an allusion to the difference in the size of farmers and their capacity to engage in a lockout given their access to silo-bags—originally devised as a savings mechanism to have control over the price of sales—as we had mentioned and described by Millan, "many inhabitants of the town thought that the rural producers performing road blockades did not lose their harvest and thus they had a 'remainder' [meaning they could resist financially] to continue in the fight against the export tax. Yet, the situation of retail shops and that of workers directly or indirectly linked to agricultural activities, whose income declined during the conflict and could not count on the value of grains to sell later in order to pay for their expenditures, was different. This assumption was reinforced by the presence of 'silo-bags', such as those that we could see on the lots next to the town in one of our visits. However, the situation differed across producers due to the different size of their farms and their source of income, which shaped their positions vis-à-vis the protest." (146)

The difference between larger and smaller agricultural producers is explained by a dairy farmer and his son in an interview (Millán 2010, 146):

> Son: *"You needed storage facilities with towers before, which are very expensive. Now, the silo-bags are cheap.*
>
> Interviewer: "*They sell less and when they need it as a form of savings…"*
>
> Father: *"Yes, like a savings mechanism. Instead of money they have soybeans, they sell 10 tons…"*
>
> Son*: "Yes, you gave it to the cooperative before, but the cooperative after 90 days charged you for the storage…but with the silo-bags you can have it for a year…and you sell it when the price is good and the price of the day is what matters. That's why most of them have those 'sausages.'"* [referring to silo-bags]
>
> Interviewer*: "But is this available to a small farmer?*
> Son: *"In this area, it's for people with 200 hectares or more."*

In our own interviews, farmers said that the ideal size of the farm for using silo-bags depended on the area and the access to financing, which allowed the ability to hoard waiting for a better market condition. In other cases, 100 hectares were considered sufficient since the cost was between 2 and 4 dolls per ton of soybean and the transportation cost declined after the harvest.

D.2 Active Citations from Interviews

1. Fn. 4: Oscar Solis, Undersecretary of Added Value of the Ministry of Agriculture, April 15, 2014; and Gabriel Delgado, former Secretary of Agriculture, Buenos Aires, December 12, 2015 [link to citation].

2. Fn. 5: Oscar Solis, Undersecretary of Added Value of the Ministry of Agriculture, April 15, 2014 [link to citation].

3. Fn. 10: Alberto Casey, former leader of the "self-organized" (*autoconvocados*), Fundación Barbechando, Buenos Aires, July 2, 2015 [link to citation].

4. Fn. 11: Martín Rapetti, Vice-President of the CRA, July 14, 2015 [link to citation].

5. Fn. 13: Jorge Solmi, Vice-President of FAA, Buenos Aires, July 2, 2015; Pedro Peretti, Executive Director of FAA, Buenos Aires, July 15, 2015; and Carlos González, local representative and FAA dairy commissioner, Buenos Aires, April 14, 2015 [link to citation].

6. Fn. 14: Pedro Peretti, Executive Director of FAA, Buenos Aires, July 15, 2015; and Carlos González, local representative and FAA dairy commissioner, Buenos Aires, April 14, 2015 [link to citation].

7. Fn. 15: Jorge Solmi, Vice-President of FAA, Buenos Aires, July 2, 2015; Pedro Peretti, Executive Director of FAA, Buenos Aires, July 15, 2015; Carlos González, local representative and FAA dairy commissioner, Buenos Aires, April 14, 2015; and Gabriel Delgado, former Secretary of Agriculture, Buenos Aires, December 12, 2015 [link to citation].

8. Fn. 16: Pedro Peretti, Executive Director of FAA, Buenos Aires, July 15, 2015; and Carlos González, local representative and FAA dairy commissioner, Buenos Aires, April 14, 2015 [link to citation].

9. Fn. 17: Juan P. Merbilhaa, former president of CARBAP, Buenos Aires, July 28, 2016 [link to citation]

10. Fn. 18: Dardo Chiesa, ex-president of the CARBAP and current president of the CRA, April 12, 2015) and Martín Rapetti, Buenos Aires, July 14, 2015 [link to citation].

11. Fn. 19: Elgidio Mailland, president of CONINAGRO, and Daniel Assef, executive director of CONINAGRO, Buenos Aires, March 17, 2015 [link to citation].

12. Fn. 20: Elgidio Mailland, president of CONINAGRO, Buenos Aires, March 17, 2015 [link to citation].

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