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DISRUPTIVE INNOVATION AND NICHE EMERGENCE: A LONGITUDINAL, MULTI-NATION ANALYSIS OF BIOAGRICULTURE

J. Michael Geringer, Ph.D.
O'Bleness Professor of International Strategy & Director of Research
College of Business - Ohio University
Athens, OH 45701 USA
Ph: +1.805.459.1383 email: Geringer@ohio.edu

Ikenna Uzuegbunam
Assistant Professor of Strategy and Entrepreneurship
College of Business - Ohio University
Athens, OH 45701 USA

Abstract

To better understand the theory of disruptive innovation, this study provides a longitudinal, multi-nation empirical investigation of the influence of agricultural biotechnology (agbiotech) adoption in an established industry context, the agricultural commodities industry, over 1996-2015. By combining industrial organization economics and institutional theory perspectives, we propose that the adoption of disruptive innovation in the agricultural industry context will (1) negatively impact relative proportions of established segments in the industry, and (2) positively influence the development and growth of new niches in the industry. Furthermore, we investigate how these effects are affected by the institutional context of innovation adoption by leveraging a cross-country sample. This paper extends the growing literature on disruptive innovation by highlighting the broader effects of disruptive technological change in a novel industry context. Specifically, we consider the proposition that in addition to disruption of existing market segments, a disruptive innovation could create opportunities for the emergence of adjacent niches. This study also contributes to the literature by emphasizing the institutional dimensions of disruptive innovation. We submit that the findings documented in this paper have implications for firms and policy makers in different institutional environments.

Key words: agricultural biotechnology, disruptive innovation, institutions, niche

Competitive Paper

DISRUPTIVE INNOVATION AND NICHE EMERGENCE: A LONGITUDINAL, MULTI-NATION ANALYSIS OF BIOAGRICULTURE

Strategy and innovation scholars have long been interested in understanding when new entrants win during disruptive technological change, paying less heed to the potential of multiple equilibria (Adner and Zemsky, 2005). Prior research suggests that certain types of innovation (i.e. disruptive innovation) can *creatively destroy* established firms and industries (Christensen, 1997; Darneels, 2006; Henderson and Clark, 1990; Schumpeter, 1942; Tushman and Andersen, 1986). Typically, because it is initially judged as inferior to mainstream offerings along the dimensions of performance that are most relevant to mainstream customers, disruptive innovation introduces different performance criteria from mainstream (or sustaining) innovation (Adner, 2002; Adner and Zemsky, 2005; Christensen, 1997).

While researchers have shown mounting evidence that disruptions can occur in a variety of industries, including disk drives, telecommunications, and healthcare, key issues remain unresolved. First, prior inquiries have mainly focused at the firm and interfirm level, ignoring broader industry trends that occur over the lifecycle of the adoption of disruptive innovation. While concentrating on the question of when new entrants with a disruptive innovation would win is valuable, it ignores the potential of a multi-stage, positive sum game, where disruptions could lead to a win-win scenario for different segments of the industry, over the long run. For example, the literature is yet to account for potential that the adoption of a disruptive innovation could provide legitimacy for adjacent niches in the industry to co-develop. Second, though some prior studies have delved into the institutional context of innovation adoption in general (e.g. Abrahamson and Rosenkopf, 1993; Hargadon and Douglas, 2001; Westphal, Gulati, and Shortell, 1997), our understanding of the institutional environment of disruptive innovation remains limited. This gap in the literature is significant because institutional forces can either legitimize or delegitimize a disruption. For example, regulatory regimes that govern agricultural biotechnology in the European Union tend to be more restrictive than comparable regimes in the United States (Lynch and Vogel, 2001).

To better understand the theory of disruptive innovation, this study provides a longitudinal, multi-nation empirical investigation of the influence of agricultural biotechnology (agbiotech) adoption in an established industry context, the agricultural commodities industry, over 1996-2015. By combining industrial organization economics and institutional theory perspectives, we propose that the adoption of disruptive innovation in the agricultural industry context will (1) negatively impact relative proportions of established segments in the industry, and (2) positively influence the development and growth of new niches in the industry. Furthermore, we investigate how these effects are affected by the institutional context of innovation adoption by leveraging a cross-country sample.

This paper extends the growing literature on disruptive innovation by highlighting the broader effects of disruptive technological change in a novel industry context. Specifically, we consider the proposition that in addition to disruption of existing market segments, a disruptive innovation could create opportunities for the emergence of adjacent niches. This study also contributes to the literature by emphasizing the institutional dimensions of disruptive innovation. We submit that the findings documented in this paper have implications for firms and policy makers in different institutional environments.

BACKGROUND AND HYPOTHESES DEVELOPMENT

Consistent with prior predictions and evidence (e.g. Adner and Zemsky; Christensen, 1997), we expect that disruptions will occur in an industry when new entrants in an industry pursue a high-volume, low-price strategy that enables speedy market penetration into established segments. That is, disruptive innovations though the initially underperform sustaining innovations, can offer greater cost advantages to customers that will enable their quick adoption. Consider the context of agbiotech. Through the applications of recombinant DNA technology and genetic engineering techniques, agbiotech seed firms can offer seed varieties that have the potential to control pests, manage physical stress on plants, increase yields (Graff, Ruasser and Small, 2003), thus decreasing the overall costs for farmers that adopt these innovations. In the case of agbiotech, the disruptive effects are further facilitated by the disruptive business model of agbiotech seeds, which receives wide protection from various intellectual property mechanisms. This is in contrast to traditional seeds, which did not have the same level of intellectual property protection. Therefore, disruptiveness of an innovation can be measured relative to existing business models in an industry (Christensen, 2006).

Proposition 1: Agricultural biotechnology (agbiotech) innovation adoption will have a negative (disruptive) relationship with size and growth of established segments in the traditional agricultural commodities industry.

Building upon proposition 1, we consider how institutional differences will account for the extent and rate of adoption of disruptive innovation. First, we suggest that supportive institutional mechanisms (e.g. intellectual property rights, regulatory) will provide greater incentives for disruptive innovation, especially in an industry that is traditionally viewed as low technology. To help illustrate this point, we highlight critical differences between relevant institutional mechanisms in the United States (US) and countries in the European Union (EU).

When compared to other countries, the United States provides highly supportive intellectual property regimes for agbiotech innovation protection. Crops can be protected using utility patents or plant patents, which is granted by the United States Patent and Trademark Office (USPTO); or through plant variety protection certificates administered by the United States Department of Agriculture (USDA; Graff *et al.,* 2003). Prior research shows that existence of multiple intellectual property platforms for protecting innovation is an important factor in tightening the appropriability regimes, providing great incentives to the innovator (Teece, 1986). In addition, labeling requirements of agbiotech foods tend to be minimal in the US, while the EU and a number of member states have widely instituted strict labeling requirements. By 2001, the US was already growing 75% of all agbiotech crops whereas the EU had practically no agbiotech crops in production at the same time (Lynch and Vogel, 2001). We therefore propose that these differences in regulatory forces between the United States (US) and countries in the European Union (EU) have led to dramatically different patterns in the adoption of agbiotech innovation.

Hypothesis 1a: The nature and extent of the disruption associated with agbiotech innovation is moderated by institutional context such that agbiotech-promoting institutional contexts (e.g. US) will experience more disruption of the existing segments than will agbiotech-inhibiting institutional contexts (e.g. EU).

We also suggest that institutional differences between developed and emerging market countries (EMCs) will also account for systematic differences in the trajectories of disruptive innovation. EMCs tend to be characterized by institutional voids (e.g. voids in regulatory, legal and intellectual property frameworks), which tend to inhibit initial development and adoption of disruptive innovation. However, we also expect that EMCs would be fast followers and likely to adopt agbiotech innovation at a faster rate than developed countries such as the United States. This is because EMCs tend to have comparably, higher rates of food insecurity and poverty, which provides economic incentives for quicker adoption of *proven* disruptive innovation. In particular, the cost advantages demonstrated by agbiotech innovation in pioneering countries (e.g. US) are likely to be appealing to potential adopters in EMCs. Indeed, some initial accounts suggest that the adoption rate of agbiotech crops in EMCs is more than twice the adoption rate in developed countries (i.e. 11% vs. 5%; Juma, 2012). In other words, "disruptive innovation tends to create transformational growth, *opportunity for underdogs, and greater access for the less fortunate and lower costs*" (Thurston, 2014). In sum, we propose that EMCs will be quick followers and more rapid adopters of agbiotech innovation.

Hypothesis 1b: EMCs (e.g. Argentina, Brazil) will be institutional fast followers in the adoption of agbiotech innovation but will have steeper adoption curves than institutional pioneers in developed markets (e.g. US).

Disruptive innovation often starts in niche markets before overcoming mainstream markets (Adner and Zemsky, 2005). We suggest that the adoption of disruptive innovation, which is facilitated by institutional forces, can signal opportunities for adjacent niches in the industry to emerge and grow. Specifically, as agbiotech innovation starts expanding from niche markets into mainstream markets (enabled by cost advantages), it provides opportunities for other niches in the agricultural commodities industries (e.g. the certified organic niche) to start gaining legitimacy by virtue of their differentiation from agbiotech. In particular, the rules and frameworks that constrain diffusion of agbiotech (James, 2013) due to environmental concerns (Juma, 2012), could provide opportunities for the certified organic niche to thrive.

Hypothesis 2: Agbiotech innovation adoption will have a positive relationship with the development of an organic niche presence.

We also argue that when one crop gains adoption in one country, it would become easier form another crop to gain adoption as well. That is, adoption in one product category (e.g. agbiotech corn) legitimizes adoption in adjacent product categories (e.g. agbiotech soybeans).

Hypothesis 3: The level and rate of agbiotech adoption in one product category (e.g. biotech corn) is positively associated with the level and rate of adoption in a related agbiotech product category (e.g. biotech soybeans) in the same institutional context.

METHODS

Data and Sampling Approach

The sampling frame for this study includes nine major agricultural producing countries that have varying degrees of adoption of agricultural biotechnology between the time periods, 1996-2014. Specifically, we included countries that were either a (1) top ten agricultural producers of the crop categories of interest in this study (i.e. corn, soybeans, cotton), or (2) top agricultural producers in Europe (our proposed control group). The countries in our final sample include the United States, Canada, Argentina, Brazil, Germany, Poland, Spain, India and China. Our estimates based on data collected from the United States

Department of Agriculture (USDA), show that four of these countries: Argentina, United States, India and China account for approximately 60% of global cotton production; Argentina, Brazil, United States and Canada account for upwards of 70% of global soybeans production; and six of these countries account for 55% of global corn production. [1]

We sampled these countries on their rates of adoption of agricultural biotechnology adoption in three major crops, cotton, soybeans and corn. These three crops represent the highest adoption rates of agbiotech according to ISAAA (James, 2013). The three main sources of these data are United States Department of Agriculture (USDA)—Economic Research Service and the Foreign Agricultural Service, Food and Agriculture Organization (FAO) and the International Service for the Adoption Agri-biotech Applications (ISAAA). Two of the authors checked this data for reliability across data sources. In some instances, we excluded countries, or years with questionable data. For all analysis, we rely on the most conservative data across our sources.

Variables and definitions

The primary dependent variables for this study are annualized data on the amount of certified organic land in each country, indicating organic niche presence. The main independent variable for the study is annual data indicating the percentage of genetically modified seeds that have been adopted for each product category (i.e. cotton, soybeans, corn), in each country. Finally, we coded a series of dummy variables that indicate variations in the country context, especially as it applies to the specific phenomenon of agricultural biotechnology adoption.[2] These variables indicate fast followers in agbiotech adoption (i.e. Argentina or Brazil =1, otherwise = 0) and pioneering countries in agricultural biotechnology adoption (i.e. USA = 1, otherwise = 0). Also, a theoretically derived selection of control variables was included in the analysis to rule out alternative explanations.

Analytical Approach

We conduct two sets of analyses for this paper. First, we conduct within country bivariate correlation analyses for various hypotheses in our study. Then, we conduct regression analysis. To account for the possible simultaneity between agbiotech adoption and organic niche presence, we employ a simultaneous equation model for our regression analysis. Specifically, we use a three-stage least squares (3SLS) system and the seemingly unrelated regression option (SURE) for cross-equation variation in Stata. This system of equation allows us to estimate the organic niche presence simultaneously as a function of agbiotech adoption and agbiotech adoption as a function organic niche presence. The independent variables lag the dependent variable by one time period (i.e. one year). The system of equations can be expressed as follows:

$$\textit{Organic Niche Presence}_{\,t} = \textit{Agbiotech Adoption}_{\,(t-1)} + x_1 + x_2 + \ldots + x_k + \varepsilon_1 \qquad (1)$$

$$\textit{Agbiotech Adoption}_{\,t} = \textit{Organic Niche Presence}_{\,(t-1)} + x_1 + x_2 + \ldots + x_k + \varepsilon_2 \qquad (2)$$

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[1] We calculated these percentages by collecting total output of cotton, soybeans and corn for these countries and determining their proportions relative to the world output on the respective crops for the corresponding years. These numbers and the relevant charts are available from the authors, upon request.

[2] We relied extensively on the annual reports from leading industry association for biotechnology adoption (i.e. ISAAA) in determining an appropriate coding scheme for different countries. The ISAAA reports suggest that the United States (from a market perspective) is an early adopter of agbiotech innovation, while Argentina and Brazil are fast followers in adopting these innovations.

PRELIMINARY RESULTS

Results from bivariate correlation analyses provide initial support for some of our hypotheses. We conducted these bivariate correlation analyses for different subsamples. Bivariate correlations are presented in Tables 1a-1e. We found positive and statistically significant bivariate correlations between agbiotech crop adoption (i.e. cotton, soybeans, corn) and organic niche presence across different countries in our sample. These findings are consistent with our predictions in hypothesis 2. Also, we found that correlations between biotech cotton, soybeans and corn are positive and significant at the 1% level, for the US sub-sample. When compared to within-country correlations for other countries, we find similar patterns for Argentina, and the EU, but less so for Canada. We claim that this provides some initial support for hypothesis 4.

The results of the simultaneous regression analysis of all countries in our sample also provide additional support for our hypotheses. The sample sizes for these regressions are relatively small (35-68, due to missing data and because not all crops are relevant for all countries in our sample). First, we find strong support for hypothesis 1a, which states that the effect of disruption will be more substantial in agbiotech promoting institutional contexts such as the US. The coefficient of the US dummy predicting the percentage of agbiotech crops relative to total (for cotton, soybeans, corn) is positive and significant at the 1% level. This is an indication of greater disruption in the US context. This result is striking considering the small power in our regressions. We also find support for hypothesis 1b, which states that EMCs will be fast followers relative to developed countries. The dummy variable indicating EMCs is negative and significant at the 1% level when predicting agbiotech corn adoption; negative and statistically significant at the 5% level when predicting agbiotech adoption in soybeans; and negative and statistically significant at the 10% level for cotton. Since cotton is a non-food crop, these findings together support our claim about the relevance of the economic environment in the adoption of agbiotech in EMCs. Also, charts of agbiotech adoption show steeper curves for EMCs than the US, as hypothesized. We therefore claim support for hypothesis 1b.[3]

We find additional support for hypothesis 2 in our simultaneous equation regressions. When we regress (in separate models), agbiotech cotton, corn and soybeans on organic niche presence, we find positive and statistically significant relationships (1% level for corn and soybeans; 5% - 10% for cotton depending on models). Broadly, these results support our claims in hypothesis 2.

CONCLUSION

The contributions of this research are threefold. First, the study helps highlight the impact of disruptive innovations in a novel industry context –the agricultural commodities industry. Much of the prior empirical work in this area has focused on studying disruptions in computer related sectors such as disk drives (e.g. Christensen, 1997). We contribute to the thriving work on disruptive innovation by highlighting these effects in a more traditional sector, the agricultural commodities sector. Second, this research provides some initial insights into the roles of institutions in shaping the adoption of innovation and the post-innovation structure of the industry. For instance, we highlight how emerging market countries, EMCs (e.g. Argentina) could follow a different technological trajectory than the pioneers of disruptive innovation. By extension, it is possible that agbiotech innovation in EMCs may have the potential to transform institutional frameworks in emerging markets (see

[3] These charts are available from the authors upon request.

Hargadon and Douglas, 2001), thereby filling vital institutional voids. Finally, by demonstrating the relationship between disruptive innovation and the development and growth of new niches (e.g. certified organic niche) in an established industry, we extend recent insights that consider the potential for multiple equilibria (e.g. Adner and Zemsky, 2005; Christensen, 2006). These insights also suggest the potential for coordination between different segments in shaping industry expectations and outcomes.

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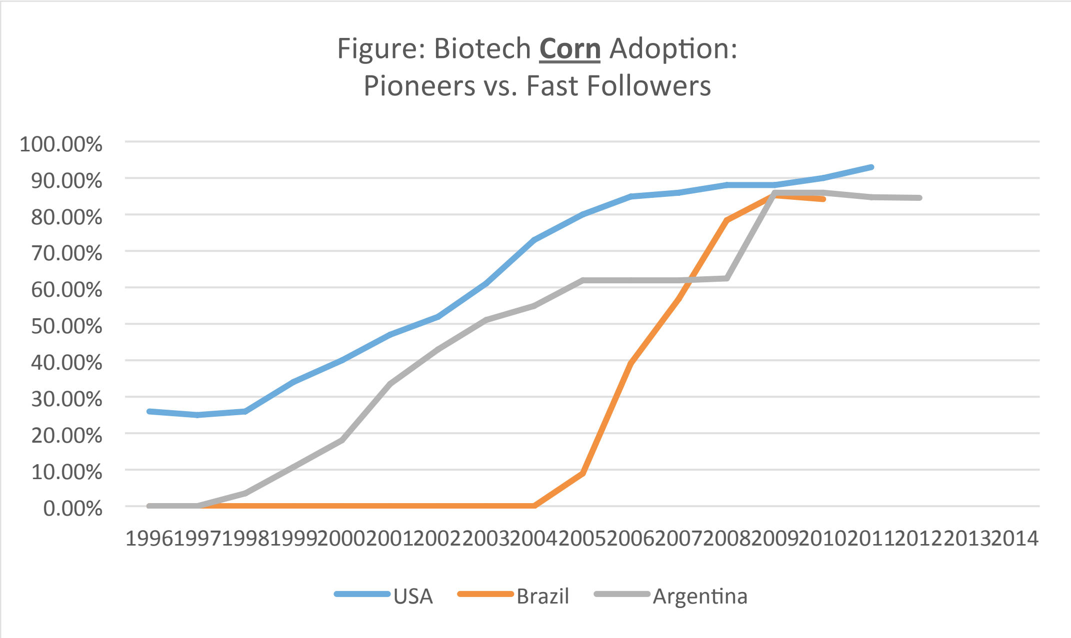
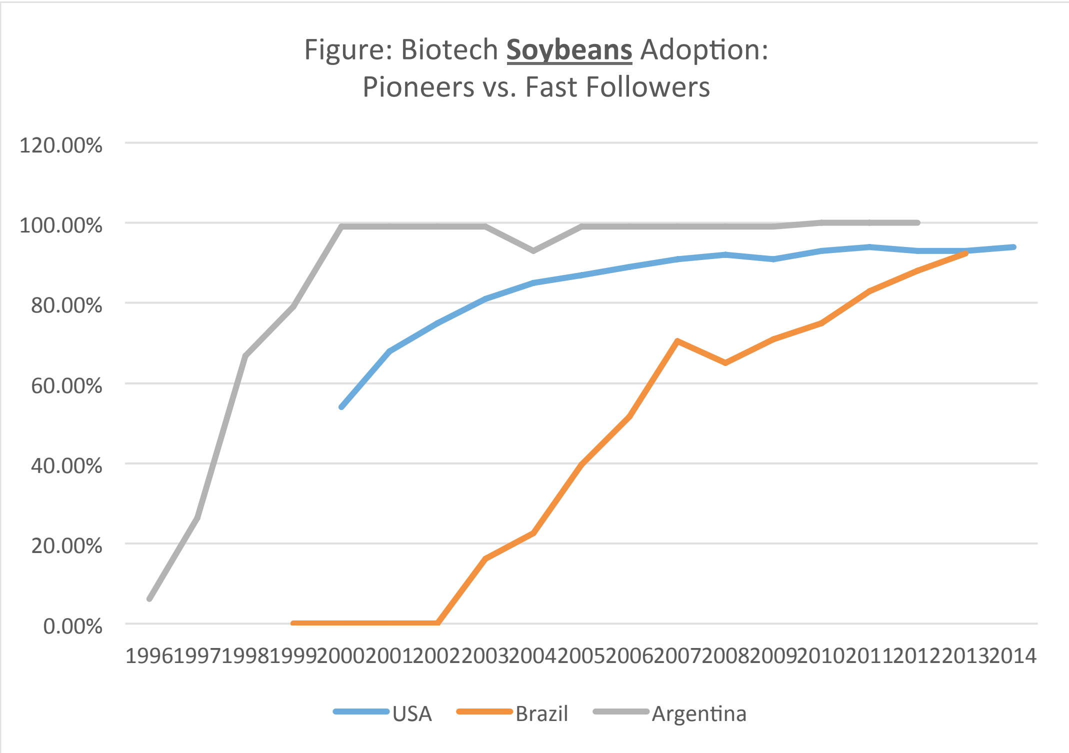
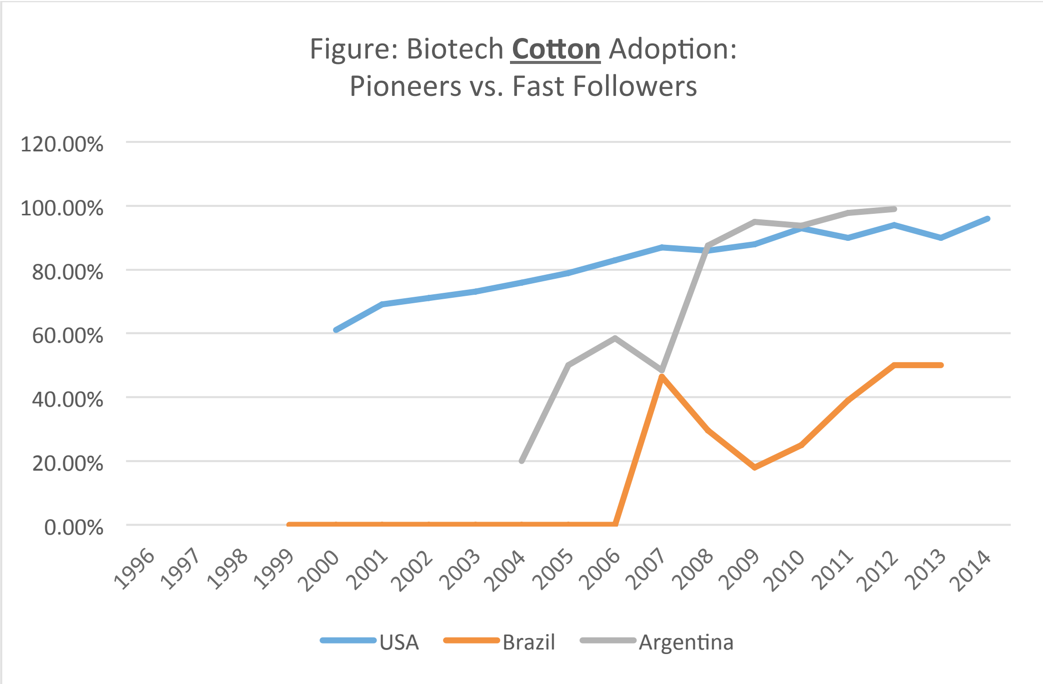
Hypothesis 1a Graphs







Hypothesis 1b Graph

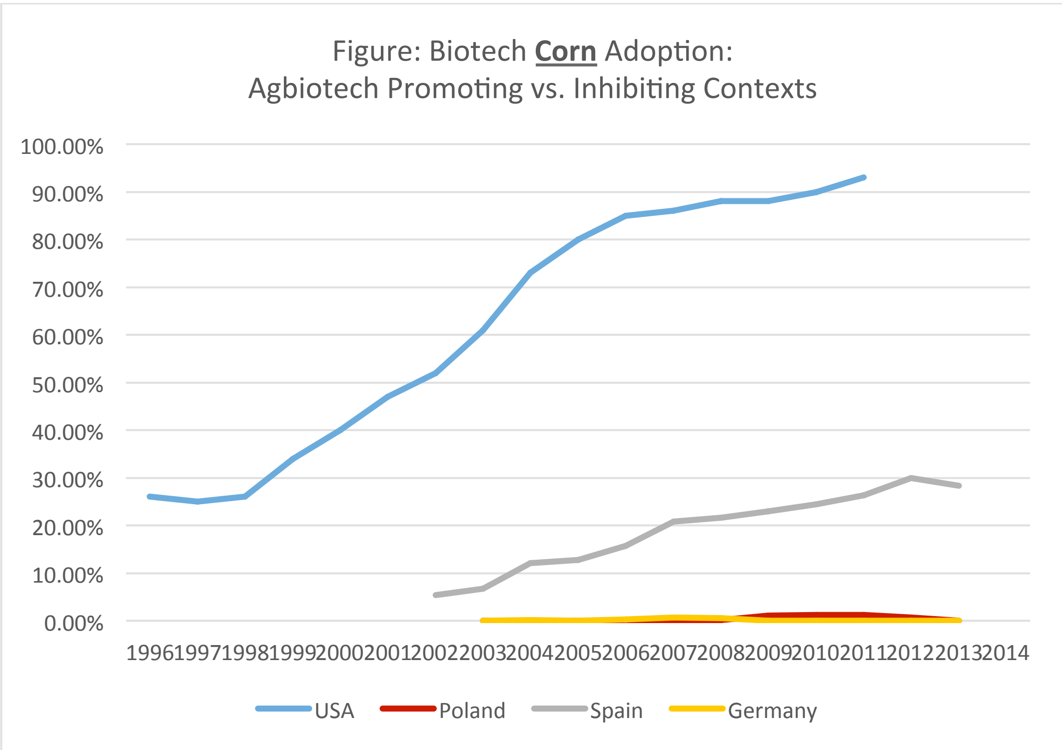


Table 1a: Summary Statistics and Correlation Matrix (Argentina)

	1	2	3	4	5	6	7	8	9
1. Biotech Cotton (Kha, t)	1								
2. Biotech Cotton Squared (Kha, t)	0.968	1							
3. Biotech Soybeans (Kha, t)	0.995	0.941							
4. Biotech Soybeans Squared(Kha, t)	0.984	0.992	1						
5. Biotech Corn (Kha, t)	0.954	0.986	0.924	0.971	1				
6. Biotech Corn Squared (Kha, t)	0.837	0.926	0.785	0.879	0.957	1			
7. Organic Land Area (Kha, t+1)	0.699	0.676	0.696	0.68	0.66	0.595	1		
8. Organic Land Area Squared (Kha, t+1)	0.699	0.714	0.684	0.71	0.694	0.642	0.965	1	
9. Time Trend (1985 =1,... 2014=30)	0.98	0.996	0.96	0.995	0.98	0.909	0.887	0.881	1
Mean	15031.61	2.83E+08	12950.28	2.03E+08	1924.889	5.71E+06	2323.81	7.67E+06	15.5
S.D.	7748.505	2.09E+08	6150.09	1.36E+08	1457.795	6.29E+06	1539.601	6.16E+06	8.803
Min	370	1.37E+05	370	1.37E+05	0	0	5.5	30.25	1
Max	24794	6.15E+08	20438	4.18E+08	4376	1.91E+07	4327.372	1.87E+07	30

Bivariate correlations greater than or equals to the absolute value of 0.66 and 0.6 are significant at the 1% and 5% levels respectively. Obs [17 - 30]

Table 1b: Summary Statistics and Correlation Matrix (Brazil)

	1	2	3	4	5	6	7
1. Biotech Soybeans (Kha, t)	1						
2. Biotech Soybeans Squared (Kha, t)	0.968	1					
3. Biotech Corn (Kha, t)	0.943	0.908	1				
4. Biotech Corn Squared (Kha, t)	0.98	0.962	0.974	1			
5. Organic Land Area (Kha, t+1)	-0.472	-0.626	-0.871	-0.841	1		
6. Organic Land Area Squared (Kha, t+1)	-0.438	-0.596	-0.867	-0.835	0.976	1	
7. Time Trend (1985 =1,... 2014=30)	0.987	0.954	0.979	0.991	0.435	0.364	1
Mean	14588.56	2.61E +08	8201.386	8.37E+07	744.853	6.07E+05	15.5
S.D.	7309.4	2.20E +08	4445.295	6.65E+07	235.528	2.66E+05	8.803
Min	3000	9.00E +06	1300	1.69E+06	100	10000	1
Max	26900	7.24E +08	12900	1.66E+08	932.12	8.69E+05	30

Bivariate correlations greater than or equals to the absolute value of 0.94 and 0.6 are significant at the 1% and 10% levels respectively. Obs. [5 - 30]

Table 1c: Summary Statistics and Correlation Matrix (Canada)

	1	2	3	4	5	6	7
1. Biotech Soybeans (Kha, t)	1						
2. Biotech Soybeans Squared (Kha, t)	0.995	1					
3. Biotech Corn (Kha, t)	0.861	0.812	1				
4. Biotech Corn Squared (Kha, t)	0.851	0.803	0.996	1			
5. Organic Land Area (Kha, t+1)	0.747	0.71	0.825	0.793	1		
6. Organic Land Area Squared (Kha, t+1)	0.756	0.721	0.83	0.801	0.998	1	
7. Time Trend (1985 =1,... 2014=30)	0.874	0.861	0.84	0.82	0.93	0.919	1
Mean	843.236	7.98E+05	868.616	7.92E+05	665.989	4.55E+05	15.5
S.D.	312.616	6.03E+05	206.556	3.79E+05	112.789	1.57E+05	8.803
Min	530	2.81E+05	633	4.01E+05	542	2.94E+05	1
Max	1408	1.98E+06	1192	1.42E+06	841.2	7.08E+05	30

Bivariate correlations greater than or equals to the absolute value of 0.8 and 0.7 are significant at the 1% and 10% levels respectively.
Obs [7 - 30]

Table 1d: Summary Statistics and Correlation Matrix (United States)

	1	2	3	4	5	6	7	8	9
1. Biotech Cotton (Kha, t)	1								
2. Biotech Cotton Squared (Kha, t)	0.997	1							
3. Biotech Soybeans (Kha, t)	0.131	0.154	1						
4. Biotech Soybeans Squared(Kha, t)	0.123	0.145	0.995	1					
5. Biotech Corn (Kha, t)	0.016	0.045	0.859	0.873	1				
6. Biotech Corn Squared (Kha, t)	0.021	0.047	0.819	0.842	0.99	1			
7. Organic Land Area (Kha, t+1)	-0.008	0.036	0.856	0.866	0.93	0.885	1		
8. Organic Land Area Sq. (Kha, t+1)	-0.022	0.024	0.837	0.851	0.945	0.908	0.989	1	
9. Time Trend (1985 =1,... 2014=30)	0.098	0.12	0.903	0.923	0.977	0.973	0.967	0.945	1
Mean	4183.822	1.78E+07	26006.02	6.92E+08	22009.18	5.88E+08	1228.349	1.83E+06	15.5
S.D.	589.497	5.08E+06	4069.471	1.98E+08	10511.77	4.54E+08	582.483	1.48E+06	8.803
Min	3260.882	1.06E+07	16241.97	2.64E+08	7971.421	6.35E+07	456	2.08E+05	1
Max	5371.053	2.88E+07	32048.85	1.03E+09	34760.54	1.21E+09	1948.946	3.80E+06	30

Bivariate correlations greater than or equals to the absolute value of 0.82 are significant at the 1%. Obs. [13 - 30]

Table 1e: Summary Statistics and Correlation Matrix Using Percentages of Biotech Adoption (United States)

	1	2	3	4	5	6	7	8
1. Biotech Cotton (%, t)	1							
2. Biotech Cotton Squared (%, t)	0.978	1						
3. Biotech Soybeans (%, t)	0.995	0.969	1					
4. Biotech Soybeans Squared(%, t)	0.973	0.984	0.982	1				
5. Biotech Corn (%, t)	0.872	0.944	0.862	0.923	1			
6. Biotech Corn Squared (%, t)	0.763	0.874	0.743	0.832	0.967	1		
7. Organic Land Area (Kha, t+1)	0.839	0.911	0.845	0.911	0.958	0.925	1	
8. Organic Land Area Squared (Kha, t+1)	0.8	0.888	0.802	0.88	0.955	0.949	0.989	1
Mean	0.651	0.544	0.674	0.585	0.523	0.379	1228.349	1.83E+06
S.D.	0.357	0.324	0.372	0.347	0.333	0.329	582.483	1.48E+06
Min	0	0	0	0	0	0	456	2.08E+05
Max	0.96	0.922	0.94	0.884	0.93	0.865	1948.946	3.80E+06

All bivariate correlations in table are significant at the 1% level

Table 2: Three Staged Least Squares (3SLS) Regression Results

VARIABLES	Model 7 **Biotech Soybeans (t+1)**	Model 8 **Biotech Soybeans (t+1)**	Model 9 **Biotech Corn (t+1)**	Model 10 **Biotech Corn (t+1)**	Model 11 **Biotech Cotton (t+1)**	Model 12 **Biotech Cotton (t+1)**
Organic Land (total organic area)	**0.00032*** **	**0.00023*** **	**0.00034*** **	**0.00023*** **	**0.00009* **	**0.00005** **
	[0.00005]	**[0.00002]**	**[0.00005]**	**[0.00002]**	**[0.00004]**	**[0.00002]**
Time Trend	-0.03596***	-0.01649*	-0.00048	0.02201***	0.01762*	0.02923***
	[0.01048]	[0.00648]	[0.00971]	[0.00661]	[0.00760]	[0.00585]
Institutional Follower (LA)	**-0.40287** **		**-0.46593*** **		**-0.17394* **	
	[0.13623]		**[0.13893]**		**[0.08368]**	
Institutional Pioneer (USA)		**0.32270*** **		**0.34967*** **		**0.16600*** **
		[0.06184]		**[0.06446]**		**[0.03511]**
Constant	0.93185***	0.48980***	0.00076	-0.40956***	0.33187**	0.09689
	[0.16965]	[0.12099]	[0.15841]	[0.12067]	[0.12109]	[0.10699]
Observations	40	40	68	68	35	35
R-squared	0.533	0.658	0.402	0.538	0.378	0.579

	Total Organic Land (t+1)	Total Organic Land (t+1)	Total Organic Land (t+1)	Total Organic Land (t+1)	Total Organic Land (t+1)	Total Organic Land (t+1)
Time Trend	70.89159***	-9.80036	36.99302*	-103.63869***	37.17735	-17.59118
	[18.27144]	[26.55233]	[16.75915]	[28.06336]	[32.32734]	[78.24282]
Institutional Follower (LA)	**1,807.84377*** **		**2,008.24014*** **		**2,089.07566*** **	
	[174.12331]		**[152.27677]**		**[194.97289]**	
Institutional Pioneer (USA)		**-1,211.98285*** **		**-1,152.89540*** **		**-922.51590***
		[256.89357]		**[283.42602]**		**[433.57759]**
Biotech Soybeans (%)	**1,381.36804*** **	**3,093.38330*** **				
	[233.84021]	**[351.71958]**				
Biotech Corn (%)			**1,289.56514*** **	**3,401.45659*** **		
			[191.92496]	**[347.13724]**		
Biotech Cotton (%)					**1,402.33454****	**2,254.90559+**
					[490.74165]	**[1,205.94926]**
Constant	-939.32084**	320.52191	-52.36575	2,376.43329***	-255.49381	943.05046
	[354.91970]	[523.04803]	[289.50064]	[476.79382]	[502.65589]	[1,093.77291]
Observations	40	40	68	68	35	35
R-squared	0.837	0.560	0.803	0.303	0.784	0.171

The table reports parameter coefficient estimates $^{+}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. Standard errors are in parentheses.