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**Measuring the Contribution of Genetic Characteristics as an
Indicator of Innovation: the case of Corn in the USA, 1990-2009.**

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Measuring the Contribution of Genetic Characteristics as an Indicator of Innovation: the case of Corn in the USA, 1990-2009.

Elizabeth Nolan^{1*} and Paulo Santos²

Abstract

Intellectual Property Rights (IPR) regimes for plant breeding are generally justified on the basis that they encourage innovation. Introduction of IPR regimes for plant varieties in the United States has led to increased concentration, but it is less clear whether IPRs have promoted useful innovation, as measured by productivity of available corn hybrids. There are difficulties in finding a satisfactory measure of innovation in plant breeding, and in this paper we propose a procedure. Results from the annual corn hybrid trials conducted by 11 US universities over the 20 years from 1990 to 2009, at 365 separate locations in the 11 states, have been collated. This set of unbalanced panel data for grain corn hybrid trials has been used in a fixed effects model to estimate a production function for corn and the contribution to yield of the genetic characteristics of the corn hybrids. The Hausman Taylor estimator is then used to separate out the contribution of GM traits. Because the data are experimental, the production function can be interpreted as representing the technological frontier. The cross section is made up of the corn hybrids that were submitted for trial over the period. The fixed or unobserved time invariant effects represent the part of production which can be attributed to the characteristics of a particular hybrid. This is taken to be the contribution of the "genetics" of each hybrid to yield, and the maximum fixed or unobserved effect in any one year can be considered to represent the "frontier" of genetic contribution to increased yield.

Key Words: hybrid seed corn, GM traits, varietal change, fixed effects, random effects

JEL Codes: O33 O34

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Introduction

There has been considerable change in the structure of the plant breeding industry in the United States since the introduction of Intellectual Property Rights (IPRs) and the development of biotechnology. Investment in biotechnology was fostered by the availability of patent protection, and the development of genetically modified (GM) traits prompted mergers and acquisition activity as firms who owned traits acquired firms who owned germplasm and distribution networks, and firms who owned germplasm sought access to biotechnology. Because a number of important changes occurred at approximately the same time in the plant breeding industry, it is difficult to disentangle the links between IPRs, concentration and innovation. An increase in innovations in plant breeding might be due to changes in industry structure or changes in management rather than to the introduction of intellectual property rights (Alston and Venner 2002).

It would be interesting to determine whether increased concentration in an industry has a positive or negative effect on innovation in that industry, and whether any negative effect outweighs the possible positive effects of IPR protection. However, a necessary first step in the evaluation of the impact of the introduction of the IPR legislation is the development of a reliable measure of the contribution of genetic change, through the introduction of new varieties, to productivity. Most previous studies have used time trends to measure the effects of technological change, but this method does not allow the separation of the effect of varietal technology from improvements in management efficiency or increased use of other inputs (Traxler et al. 1995)

In this paper we address this question. We propose a method for measuring the contribution of the genetic characteristics of an individual corn hybrid to yield. We

use a large panel dataset of actual yield results from experimental field trials of corn hybrids submitted by corn breeders to the State Agricultural Extension Services of 11 United States universities over 20 years. Because we use experimental data, the estimates of individual fixed effects measure the contribution to yield of the genetic characteristics of the hybrids being tested. We map the changes in contribution of these characteristics that have occurred over 20 years as new hybrids have been introduced. Another advantage of using experimental data is that they allow us to explore other specifications of panel data models: in particular, we are able to identify the impact of the GM traits associated with each hybrid, through the estimation of a Hausman-Taylor random effects model.

There are two main limitations to our results, which we plan to address in future work. The first is that technological change should not be measured only in terms of yield, as cost savings or reduction in risk may also matter. Given that we limit ourselves to determining the part of yield increases that can be attributed to genetic change we are clearly not measuring the entire impact of technical change. The second is that we estimate one single model for a large area of the country which, for both physical and institutional reasons, may be unrealistic.

Background

The introduction of IPRs in US plant breeding has created a climate that is favourable to the development of modern agricultural biotechnology, but has also led to increased importance of private plant breeding, and continuing consolidation in the US seed industry (Alston and Venner 2002; Wright and Pardey 2006).

Private investment in plant breeding and biotechnology research that has produced genetically modified (GM) crops has focused on soybeans, corn, cotton and canola. Corn has attracted more plant breeding and biotechnology research resources

than any other crop, and has had the largest number of transgenic varieties approved for commercial use (Schimmelpfennig, Pray and Brennan 2004).

Eighty five per cent of all corn planted in the US in 2009 had at least one GM trait, and 46 per cent had stacked GM traits (USDA National Agricultural Statistics Service (NASS) 2009). Corn has also had the longest history of commercial seed breeding because of the ownership rights conferred by hybridisation. Privatisation of plant breeding occurred early in the corn seed industry, and most commercial corn hybrids have been privately bred. Mikel and Dudley (2006) demonstrated that public inbred lines were used in development of 45 per cent of new US corn inbred lines from 1980-1988, 10 per cent from 1988 to 1996, and only 2 per cent from 1997 to 2004.

While the US corn seed market was relatively unconcentrated until the 1970s, continuing mergers and acquisitions, particularly from the mid 1990s led to a situation where four companies now dominate the market. Rausser, Scotchmer and Simon (1999) suggest that, in the biotechnology era, there are four levels of marketing in the corn seed industry: traits, foundation seed, retail seed and distribution. In this paper we are concerned with the first three.

The first level relates to sales of the GM component of corn seeds. Monsanto provides the Bt (corn borer and rootworm) and RR (Roundup herbicide tolerant) genes not only to its own subsidiaries but also to Pioneer and other companies. Dow owns the Herculex insect resistance traits and Bayer owns the Liberty Link herbicide tolerant trait. In 2004, Syngenta launched the Agrisure CB (corn borer) trait, followed by the Agrisure RW (rootworm) trait in 2006. Herculex and Agrisure hybrids contain LL herbicide tolerance, and many are quadstack with RR as well. Other trait developers are not in any commercial transactions.

Before biotechnology there were two types of seed retailing, which correspond to the second and third of the categories nominated by Rausser, Scotchmer and Simon (1999). Foundation seed companies like Holden's (now owned by Monsanto) developed lines of elite seed and sold them to small distributors. Holden's germplasm is widely distributed throughout the industry and at least one of its elite lines is present in most commercial corn pedigrees (Rausser, Scotchmer and Simon 1999). Several large firms such as Pioneer, DeKalb and Garst integrated breeding and distribution of their own released varieties, leaving only a small part of the final marketing to independent but exclusive sales agents (Rausser, Scotchmer and Simon 1999). Since the marginal cost of incorporating a trait into a seed is effectively zero, the earnings from licensing the trait are almost entirely a function of market size, so

Table 1 Current Ownership of United States Seed Breeders and Distributors (Retail and Distribution Level)

	Monsanto	DuPont	Syngenta	AgReliant	Dow	Crop Production Services	Land O'Lakes
Asgrow	Heritage	Pioneer	AgriPro	AgriGold	AgriGene	DynaGro	Cenex
Campbell	High Cycle	Curry	Blaney	Callahan	Cargill	UAP	Croplan
CFS	Hubner	Alliances	CIBA	Dahlco	Dairyland	Vigoro	FFR
Challenger	ICORN	AgVenture	Elite	Great Lakes	Deltapine		Hyttest
Channel	Jung	Adler	Funks	Herried	Dow		Pickseed
Cheesman	Kruger	Frontier	Garrison	Horizon	Golden Acres		Terra
Circle	Lewis	McKillip	Garst	J M Schultz	Growers		Zimmerman
Crows	Linco	Select Seed	Golden Harvest	LG Seeds	Jacques		Alliance
DeKalb	Midwest	Spangler	Gutwein	McAllister	Keltgen		Growmark
Desoy	NC +	Beck	HyPerformer	Noble Bear	Lynks		
Didion	REA	Wilken	ICI	Producers	McCurdy		
Diener	Sieben	Burrus	NK	PSA	Mycogen		
Fielders Choice	Specialty	Doebler	Novartis	Shissler	ORO		
Fontanelle	Stewart	Hoegemeyer	Payco	Voris	Pfister		
Gold Country	Stone	NuTech	Stauffer	Wensman	Renze		
Grow Direct	Trelay	Seed Consultants	Sturdy Grow		Schillinger		
Hawkeye	Trisler	Terral	Super Crost		Shur Grow		
Heartland	Wilson				Sigco		
					Taylor Evans		
					Triumph		
					Vineyard		

that a large marketing network now complements a portfolio of traits (Rausser, Scotchmer and Simon 1999).

This partly explains the expansion of the large firms into retailing through the purchase of regional seed companies, and this expansion is continuing, with the main participants in the corn seed market today being Pioneer HiBred (DuPont), Monsanto, Syngenta and Dow AgroSciences. An indication of the extent to which the large companies have expanded into the retail market is provided in Table 1 which summarises the current ownership of the seed companies which have submitted hybrids to university trials over the past 20 years. This does not list all seed companies, but gives an indication of the breeding and distribution networks of the larger conglomerates.

Intellectual property rights, market structure and innovation

There is some evidence that the introduction of IPRs for plant varieties may have reduced research intensity¹ in plant breeding rather than encouraging innovation, and it is suggested that this may be because the introduction of IPRs has encouraged concentration (Fernandez-Cornejo and Schimmelpfennig 2004; Schimmelpfennig, Pray and Brennan 2004).

It is not clear whether increased concentration will increase or decrease research intensity as it is difficult to find a clear link between increased concentration and the rate of innovation. On one side it can be argued that high profits generated by a monopolist will allow him to hire more highly qualified personnel and to provide more finance. Economies of scale and scope in conducting research, and in obtaining and defending IPRs on research results, could increase the productivity of a unit of research and could increase research intensity. However if there is too much

¹ Defined in these papers as the annual number of field trial applications from private firms divided by private industry sales of seed for each major crop (in millions of dollars)

concentration the competitive pressure to do research may be reduced (Geroski 1994; Schimmelpfennig, Pray and Brennan 2004).

Schimmelpfennig, Pray and Brennan (2004) found an inverse relationship between concentration and research intensity for the corn industry in the United States. They also found that more concentration is associated with fewer patents. This may be because there are fewer competitors to protect intellectual property from, or because there are fewer research results to protect (Schimmelpfennig, Pray and Brennan 2004). Brennan et al. (2005) argue that leading biotech firms have the ability to decrease total industry investment in research and development (R&D) because of the concentration of patent ownership, and there are concerns that the cost of obtaining permission to use patented technology may prevent some firms participating in innovative research (Graff et al. 2004).

Measuring innovation: a brief review of the literature.

Common measures of innovative activity are R&D expenditures, patent counts and counts of major and minor innovations (Geroski 1994). Methods may include case studies and econometric analysis.

R&D expenditures are inputs into the innovation process but they may not be suitable measures of the output of the innovative process whenever the productivity of R&D varies between firms or across sectors. Innovations can also be produced without R&D (Geroski 1994). Patents protect ideas and are often thought of as a measure of intermediate output in the innovative process, but are generally an imperfect measure of innovation. Larger counts may result from a decision to seek insignificant patents rather than a few larger patents and the size or value of the “output” associated with a given patent varies enormously over different patents. Patents do not represent all of the output of R&D (Gallini 2002; Griliches, Pakes and

Hall 1986; Lanjouw, Pakes and Putnam 1998). Kolady and Lesser (2009) question whether the breeding of protected new varieties leads to more productive varieties or merely trivial reformulations, and suggest that the absence of merit standards for new varieties may imply that the plant variety protection system in the US is prone to “cosmetic breeding”. Innovation counts have the virtue of concentrating attention on the output of the innovation process. However samples of innovations are expensive to collect. There is also a problem about which unit of measurement to use.

All of these measures are likely to suffer from measurement error with a resulting misstatement of the consequences of innovative activity, and may induce a spurious positive correlation between firm size or market structure on the one hand and innovative activity on the other (Geroski 1994).

Case studies have been used to study innovation, but single cases are too small a sample to support generalisations, and are unlikely to be randomly chosen (Geroski 1994). The alternative is to use a quantitative methodology such as econometric analysis. For this kind of analysis it is necessary to have enough data, and the method is more suited to analysis of “minor” or continuing innovations, rather than on fundamental or “drastic” innovation. Development of new plant varieties would provide a good example of this type of innovation.

Isolating the specific impact of varietal technology is difficult and measurement is limited by available data. Previous studies have often used aggregate time series data, and have relied on a trend variable to account for technological change. By so doing, they are unable to separate the effect of varietal technology change from improvements in management efficiency, or increased use of other inputs (Traxler et al. 1995). Eisgruber and Schuman (1963) suggest that caution is needed when aggregated data is used for production economics analysis, as the data

are often obtained from extremely heterogeneous populations and may conceal relationships that are of significance to the analyst. It is difficult to capture yield increasing effects with a limited number of state level indices (Kolady and Lesser 2009).

One alternative to using aggregate data is to use varietal trial data, as suggested by Brennan (1984) who claims that the only reliable sources of information about relative yields are variety trials, and suggests that a measure for varietal change could be incorporated in an aggregate production function. Crop production function approaches have been used in a number of studies (for example, Alston and Venner 2002; Babcock and Foster 1991; Naseem, Oehmke and Schimmelpfennig 2005). Some studies have used varietal data but, again, have relied on a trend variable to account for changes in technology (Alston and Venner 2002; Chavas et al. 2001; Nalley, Barkley and Chumley 2008). Some previous studies use panel data, and fixed effects models, but in Nalley, Barkley and Chumley (2008), for example, the cross section elements are the locations of the trials. A time trend is still used to allow for changes in technology. Kolady and Lesser (2009) use varietal trial data, and measure changes in technology by measuring the yield of a new variety against the yield of a local reference variety. The contribution of genetic improvement to the yields of new varieties is taken to be the difference between the yield of the new variety and the change in yield of the reference variety over time.

Kolady and Lesser (2009) emphasise the extensive data needs for a careful production function analysis for crops planted over wide areas with varying localised conditions. The genetic potential of any hybrid interacts with environmental factors so that yield will tend to vary across locations and between cropping seasons, and improved germplasm and improved crop management often interact, so productivity

gains when the two are adopted simultaneously may exceed the sum of productivity gains when each is adopted independently (Heisey and Morris 2002).

Changes in experimental yields may overstate possible changes on farm, but varietal trial data from research stations do indicate the success of R&D in providing technical advances, and can best be interpreted as potential technical change (Babcock and Foster 1991; Kolady and Lesser 2009).

The limitations noted by Kolady and Lesser and Heisey and Morris are addressed as the data we use in our estimation are more detailed and more comprehensive than the data used in previous studies of which we are aware. They report yield (adjusted for moisture content) in bushels per acre for 233 899 individual trials, at 365 locations, of 20 930 hybrids submitted for trial by 430 companies. Agronomic practices and climatic conditions are also reported. The detail allows us to avoid a number of the problems mentioned in this section of our paper. It is still the case that these are experimental data, and that the yields reported are higher than those likely to be achieved at the farm level. In fact the mean yields for these trials by state are consistently above the mean yields reported by NASS (USDA National Agricultural Statistics Service (NASS) 2009), as can be seen in Appendix 1.

Data

Our dataset has been compiled from reports of actual yield results from experimental field trials of corn hybrids submitted by corn breeders to the State Agricultural Extension Services of eleven United States universities over 20 years.² These reports

² We have used the reports from the University of Illinois at Urbana-Champaign (Department of Crop Sciences University of Illinois at Urbana-Champaign), Purdue University (Department of Agronomy Purdue University), Iowa State University (Iowa State University Crop Testing), Kansas State University (Extension Agronomy Kansas State University), University of Minnesota (Minnesota Agricultural Research Station University of Minnesota)Mississippi State University (Mississippi State University Extension Service), University of Missouri (Division of Plant Sciences University of Missouri), University of Nebraska – Lincoln (Department of Agronomy and Horticulture University of Nebraska- Lincoln), The Ohio State University (Ohio State University Extension), South Dakota State University (South Dakota State University Cooperative Extension Service), and University of

have been produced annually for many years, and we specifically look at the period 1990-2009. The number of trials, by year and by state, is shown in table 2.

The main advantage of using these data is that they are produced under experimental conditions: randomisation across a variety of production conditions allows us to elicit the genetic value of the hybrid and its contribution to yield. Because we are interested in determining the production frontier, and the contribution of plant variety characteristics to output, the limitations identified in the previous section are not important. Additionally, many of the criticisms that can be pointed to production function approaches to the measurement of varietal performance are avoided by the richness of the data available, described below.

Corn hybrid performance trials

Corn hybrid performance trials are conducted annually to provide farmers, extension personnel, and private seed companies with agronomic information on corn hybrids submitted by private seed companies, and to provide unbiased performance comparisons of hybrid seed corn available in the various states. The trials are managed so as to minimise variability. They are conducted under the most uniform possible conditions, and small plots are used to reduce the chance of soil and climatic variations occurring between one hybrid plot and another. Trial specifications vary between states, but each hybrid is grown using three or four replications per site to account for field variability. Tests are planted and harvested with specialised commercial equipment modified for small plot work.

Seed companies marketing corn hybrids are invited to enter hybrids in the tests, and all producers of hybrid seed are eligible to enter. Participation is voluntary

Wisconsin – Madison (University of Wisconsin Department of Agronomy). Recent reports were available online, and earlier reports were supplied by the institutions involved.

and the test coordinators exercise no control over which hybrids are entered. Breeders specify the locations where the hybrids are to be trialled. The breeders may not, and do not always, submit all their varieties to the trials.

Not all hybrids grown are included in all tests, and the same group of hybrids is not grown uniformly at all test locations. Companies use the results from these trials for advertising purposes. They will obviously enter varieties for trial at the locations they believe are the most adequate for production, and most suited to the particular hybrid. Most of the hybrids are commercially available. Entry fees from private seed companies partially finance the tests.

The results are published to provide a source of objective information from various locations. Seed companies also conduct their own trials, and yields are reported and freely available. However the benefits of our dataset based on the university trials include the independence and hence objectivity of the tests, and the fact that results are available over a number of years. The other advantage of these tests, from our point of view, is that location-specific details of agronomic practices and climatic data are included in the reports.

Cultivation type and rotation were not reported by Ohio for 1998-2002 but the locations and agronomic practices for other years are consistent so that we have assumed that the same cultivation methods and rotation decisions were made. Indiana in some years reports only regional average yields, so we have omitted those years and those locations where individual results are not reported. This means that we have no entries for 1990-1993, and 1998-1999, and limited results for 1994-1997. Minnesota trial results for 1990 and for 1995-96 are missing and cannot be traced. The reports for Mississippi for 1995 and 1996 are missing, but some varieties were also tested in 1997, and their 1995 and 1996 yields are also reported. The University of Missouri is missing

reports for 1998 and 2000. Again some of the 1998 and 2000 results are reported in the following years. Iowa has the longest history of testing but records are incomplete. Records are complete from 2005. Professor Joe Lauer of UW Madison was able to provide us with data for individual locations for 1996-2001. The years 2002-2004 are lost. Even though we only have ten years of Iowa data the number of trials is substantial.

Table 2 Number of Trials by Year and State

Year	Illinois	Indiana	Iowa	Kansas	Minnesota	Mississippi	Missouri	Nebraska	Ohio	South Dakota	Wisconsin	Total
1990	1692			620		227	869	1356	1194	514	1515	7987
1991	1547			482	822	220	768	1209	1165	460	1222	7895
1992	1712			631	632	144	967	1191	949	541	1886	8653
1993	1819			762	561	321	937	1243	1365	573	1480	9061
1994	1749	113		614	566	282	1093	1429	1018	629	1779	9272
1995	1717	422		598		76	1319	1142	1067	593	1992	8926
1996	1444	1097	3732	529		119	1022	844	1332	515	2088	12722
1997	1189	983	3693	642	823	261	1190	1139	1004	535	2146	13605
1998	1069		3245	668	789	283	308	1169	955	590	2063	11139
1999	2095		3409	621	993	357	1223	1149	967	634	2159	13607
2000	1810	1626	3575	555	985	233	334	1333	853	556	1997	13857
2001	1739	1710	3321	671	859	315	1168	1087	844	593	1767	14074
2002	1302	1629		505	697	411	1201	1010	844	481	1765	9845
2003	1630	1155		466	735	591	1389	996	888	522	1797	10169
2004	2005	1341		672	931	770	1468	1149	1010	731	1818	11895
2005	1925	1471	2214	679	836	269	1479	1043	941	494	1803	13154
2006	1816	1193	2607	702	1190	435	1825	1023	838	640	1682	13951
2007	1778	1160	2810	932	1296	597	1529	1352	1215	588	2208	15465
2008	2020	1470	2587	1029	1039	459	1585	1201	1053	472	1641	14556
2009	1565	1241	2397	1028	940	591	1589	1184	1444	420	1669	14068
Total	33623	16611	33590	13406	14694	6961	23263	23249	20946	11081	36477	233901

Model

We have included the following groups of variables in our model.

Dependent variable

Grain yields are reported as bushels per acre of shelled grain (56 lb/bu) adjusted to a moisture content of 15.5%. As expected, the average annual yield for each state for

these trials is consistently above the average annual yield for each state published by the National Agricultural Statistics Service of the USDA.

Agronomic variables

Most states conduct early and late maturity trials, but in some cases the distinction was not made until the late 1990s or early 2000s. Some states still do not make a distinction. If there is not a specific statement that the trial is early season we have assumed that it is late. Nebraska reports on mid trials in some years – we have classified these as late. A dummy variable is used to indicate an early trial.

Missouri, Nebraska, Kansas, Wisconsin and Mississippi conduct irrigated trials, and a dummy variable is included to indicate whether a trial is irrigated. Type of cultivation is reported in some detail and it has been impossible to account for all the variations. A dummy variable has been used to indicate minimum or no till preparation, but only where this is explicitly stated. The default variable is conventional and everything other type of cultivation is included in this category.

Seven soil types are identified using dummy variables, with silt loam as the default soil. The only state that does not report soil type is Minnesota and we have used the coordinates for each trial site and the Soil Web Survey of the USDA Natural Resources Conservation Service (USDA Natural Resources Conservation Service 2010) to identify the predominant soil type in that location.

Previous crop is also reported for most locations. However, Illinois does not report on rotation, and, in a small number of other locations, the rotation is omitted. As soybean is the usual rotation crop, we have assumed that this is the previous crop where it was missing. Dummy variables have been included for corn, wheat, alfalfa, and other, with soybean as the base case.

Seeding rate has been included. Generally a seeding rate is reported, although in some states final plant population is given instead. We have used seeding rate where possible, but if this was not available we have substituted plants per acre. This is not exactly comparable, but the order of magnitude is in general similar.

We have fertilizer application in lbs per acre for most states. However, Illinois only started reporting fertilizer application rates in 2000, and Minnesota stopped reporting fertilizer rates in 2002. Iowa does not report fertilizer rates. We have therefore not been able to include fertilizer as an explanatory variable, as this would mean losing more than 40 000 observations.³

Climatic variables

In most cases the trial reports include rainfall for the growing months. If not, for example for Ohio and Iowa, there is generally a very good network of weather stations and it has been possible to extract monthly rainfall from their databases (Iowa Environmental Mesonet Iowa State University Department of Agronomy 2009; OARDC Ohio State University 2009). For those states which do not report specific rainfall figures (Nebraska includes column charts, and Minnesota does not report rainfall) we have used the database provided by the PRISM Climate Group at the University of Oregon (PRISM Climate Group Oregon State University 2009). This allows monthly rainfall, minimum and maximum temperatures to be extracted based on latitude and longitude coordinates. Some universities have reported rainfall May-September, others April-August and others April-September. We have filled the gaps for the months April-September from the PRISM database. As temperature is likely to be less local than rainfall, we have extracted minimum and maximum monthly temperatures April-September from the PRISM database. We have also followed

³ It would have been useful to include pesticide and herbicide application rates. However the variety of different combinations that are possible and that have been used over the past 20 years is immense.

Alston and Venner (2002) in including a cross term for rainfall and average maximum monthly temperature for the growing season.

Other dummy variables

We have included dummy variables to indicate the state where the trial was conducted. This is to allow for differences in method in each state where the differences have not been identified by the other included variables. We have also included dummy variables for year of trial to account for other factors that may have influenced the trial results in a particular year.

Hybrid identifiers and GM traits

The trial reports provide the name of the company submitting the hybrid for trial, the name of the hybrid, and, since the introduction of genetically modified hybrids, the GM traits associated with each hybrid. Since some quite different hybrids have the same number, we have identified each separate hybrid by combining the name of the submitting company and the name of the hybrid. It is this variable that we have used to create dummy variables for our cross section.⁴

We also have details of the GM traits associated with each hybrid. We have identified the presence of these traits using dummy variables, and have also created dummy variables to indicate the combinations of traits where traits are stacked. The base case is no GM traits.

⁴ In some cases a hybrid will have the same name, but a different submitting company in consecutive years. For example, Keltgen, Lynks and Mycogen all submitted a hybrid with the same name in different years. Mycogen took over these companies in the early to mid 1990s, so we have assumed that these varieties are in fact the same, and have renamed the hybrid identifier accordingly. Kruger Seed Company has at times submitted seed under the company names Kruger, KSC/Challenger, Circle and Desoy. Where the hybrid number is the same, and the submitting company has changed, but is known to be affiliated with the previous submitting company, we have considered the hybrids to be identical.

Methodology

We estimate, using Stata, a linear production function to determine the contribution of the genetic characteristics of individual corn hybrids. Because hybrids change over time, it is appropriate to treat the data as unbalanced panel data. The time series component of the panel data is the year of the trial. The cross section is made up of the 11 731 hybrids that were tested over the 20 year period and for which we have, at least, five observations.⁵ The dependent variable is yield in bushels per acre. The quantitative independent variables are seeding rate, rainfall for each of the months April to September, and average minimum and maximum temperatures for the same months. Dummy variables are used to indicate the state where the trial was held, soil type, cultivation type, previous crop, whether the trial is early or late, and whether or not irrigation was applied. A dummy variable for year of trial was also included to account for any year specific occurrences that were not accounted for elsewhere in the data. We have also included dummy variables to indicate the GM traits for each hybrid, and the degree of stacking of traits. For the remainder of this section we draw from material contained in Verbeek (2009), Greene (2003), Hausman and Taylor (1981) and Cameron and Trivedi (2010).

Panel data allow us to combine variation across units and over time, and allow for different intercepts to accommodate cross sectional heterogeneity. Including a dummy variable for each cross sectional element allows each of these elements to have a different intercept. All variables can be indexed with an i for the cross sectional individual and a t for the time period. The standard linear regression model can be written as

$$(1) \quad y_{it} = \beta_0 + x'_{it}\beta + \varepsilon_{it}$$

⁵ The initial number of individual hybrids was 20930.

where x_{it} is a K-dimensional vector of explanatory variables which does not contain an intercept term. This imposes that the intercept β_0 and the slope coefficients are identical for all individuals and time periods. The error term in (1) varies over individuals and time, and captures the unobservable factors that affect y_{it} . Given that with panel data there are repeated observations for the same individual, it is unrealistic to assume that the error terms from different periods are uncorrelated, so that standard errors for OLS tend to be misleading in panel data applications.

A random effects model assumes that

$$(2) \quad \varepsilon_{it} = \alpha_i + \mu_{it}$$

where μ_{it} is assumed to be homoskedastic and not correlated over time, and α_i is time invariant and homoskedastic across individuals. This model assumes that the observable regressors in x_{it} are not correlated with the unobserved characteristics in both α_i and μ_{it} . This may be restrictive as unobserved characteristics may be correlated with independent variables. In a fixed effects model it is possible to address the problem by including an individual specific intercept term in the model. The model can be written as

$$(3) \quad y_{it} = \beta_0 + \alpha_i + x'_{it}\beta + \mu_{it}$$

where α_i ($i = 1, \dots, N$) are fixed unknown constants that are estimated along with β , and where μ_{it} is assumed to be independently and identically distributed (i.i.d.) over individuals and time. These fixed effects, α_i , capture all unobservable time invariant differences across individuals, and consistent estimation does not impose that α_i and x_{it} are uncorrelated.

Fixed Effects versus Random Effects Models, and the Hausman Taylor Estimator

We first estimate a fixed effects model, and consider that the fixed effect for each variety represents the part of production of that variety which can be attributed to its

fixed characteristics – that is, by definition, its genetics. The fixed, or unobserved, effect is in fact the amount in bushels per acre by which the contribution of the individual hybrid’s “genetics” is above or below the contribution of the “genetics” of the mean of all fixed effects. It should be noted that for the purposes of this study “time invariant” should be read as “time and trial invariant” as there may be a number of trials of the same hybrid at different locations in the same year. The hybrids tested vary each year, and we are particularly interested in the effect of the introduction of new varieties.

Given that we estimate this model with a common intercept (that measures the average output of all varieties), the fixed effect estimates the contribution of a specific variety to output and the frontier in year t can be written as

$$(4) \quad F_t = \max \{ \max_{t-1} \alpha_i, \max_t \alpha_i \}$$

where the first term within parenthesis makes clear that when the maximum fixed effect in one year is less than that in the previous year, we assume that the better performing hybrid is still available commercially, even though it has not been submitted for trial. With this estimate of the frontier, the change in the maximum fixed effect gives an estimate of technical change that is free of the difficulties of interpretation associated with a time trend. This provides one measure of innovation in the corn seed industry.

One drawback of the fixed effects model is that time (time and trial) invariant characteristics of the individuals in the cross section are absorbed into the fixed effects. This means that with a fixed effects model it is not possible to estimate the contribution to yield of the GM traits of a hybrid. The random effects model would allow us to find the coefficients for the GM traits. However, as mentioned above, the random effects model is based on the assumption that the unobserved individual

specific effects, α_i , are uncorrelated with the included variables, x_{it} . Given that the results of our fixed effects model indicate that we should reject the null hypothesis that the independent variables are not correlated with the unobserved effects, a random effects model does not appear to be appropriate.

The Hausman and Taylor (1981) estimator for the random effects model suggests a way of overcoming the problem with the random effects model while allowing the effect of the observed time invariant characteristics, in this case the GM traits, to be identified (Greene 2003). The Hausman Taylor estimator fits panel data random effects models in which some of the covariates are correlated with the unobserved individual level random effect. The estimators are based on instrumental variables. The Hausman Taylor estimator, like the fixed effects model, assumes that some of the explanatory variables are slightly correlated with the individual level random effects, α_i , but that none of the explanatory variables are correlated with the idiosyncratic error, μ_{it} .

A random-effects model with four groups of explanatory variables could take the form

$$(5) \quad y_{it} = \beta_0 + x'_{1it}\beta_1 + x'_{2it}\beta_2 + z'_{1i}\delta_1 + z'_{2i}\delta_2 + \alpha_i + \mu_{it}$$

where the x variables are time varying and the z variables are time invariant. α_i is the unobserved, panel level random effect that is assumed to have zero mean and finite variance σ^2_α and to be i.i.d. over the panels; μ_{it} is the idiosyncratic error that is assumed to have zero mean and finite variance σ^2_μ and to be i.i.d. over all the observations in the data; β_1 , β_2 , δ_1 and δ_2 are coefficient vectors, and $i = 1, \dots, N$, where N is the number of panels in the sample and, for each i , $t=1, \dots, T_i$. Because x_{2it} and z_{2i} may be correlated with α_i , simple random effects estimators are generally

not consistent for the parameters in this model. Because the within (fixed effects) estimator removes the α_i by mean differencing the data before estimating β_1 and β_2 , it is consistent for these parameters. However, in the process of removing the α_i , the within estimator also eliminates the z_{1i} and the z_{2i} . Thus it cannot estimate δ_1 or δ_2 .

The Hausman Taylor estimator solves this problem by assuming that the variables with index 1 are uncorrelated with both α_i and μ_{it} whereas the variables x_{2it} and z_{2i} are correlated with α_i but not with any μ_{it} . Under these assumptions the fixed effects estimator would be consistent for β_1 and β_2 , but would not identify the coefficients for the time invariant coefficients. Hausman and Taylor (1981) suggest that equation (4) be estimated by instrumental variables using as instruments x_{1it} , z_{1i} and $x_{2it} - \bar{x}_{2i}$, \bar{x}_{1i} . If it is assumed that certain variables among the x' and z' are uncorrelated with α_i , then conditions may hold so that all of the β s and δ s may be consistently and efficiently estimated. The columns of x_{it} which are uncorrelated with α_i can serve two functions because of their variation across both individuals and time. Using deviations from individual means they produce unbiased estimates of the β s and using the individual means they provide valid instruments for the columns of z' that are correlated with α_i . That is the exogenous variables serve as their own instruments, with x_{2it} instrumented by its deviation from individual means as in the fixed effects approach, and z_{2i} instrumented by the individual average of x_{1it} . Identification requires that the number of variables in x_{1it} is at least as large as that in z_{2i} .

This estimator allows us to identify the coefficients of time invariant variables, even though the time varying regressors are correlated with α_i . The time averages of those time varying regressors that are not correlated with α_i are used as instruments

Table 5 Hausman Taylor Estimation

	Coef.	Std. Err.	z	P> z		Coef.	Std. Err.	z	P> z
Time Variant exogenous					Dummy variables for year with 1990 as base				
Seeding rate ('000)	2.731	0.000	87.630	0.000	1991	-5.713	0.731	-7.820	0.000
No or minimum till	-7.317	0.273	-26.770	0.000	1992	1.244	0.812	1.530	0.126
Previous crop (soybean as base)					1993	-30.220	0.849	-35.600	0.000
Corn	-5.701	0.247	-23.080	0.000	1994	10.771	0.776	13.890	0.000
Wheat	-3.435	0.324	-10.610	0.000	1995	-9.627	0.908	-10.600	0.000
Alfalfa	2.595	0.593	4.380	0.000	1996	1.962	0.785	2.500	0.012
Other	-4.771	0.395	-12.070	0.000	1997	-1.022	0.795	-1.280	0.199
Monthly rainfall					1998	15.771	0.918	17.180	0.000
April	5.107	0.453	11.270	0.000	1999	1.636	0.937	1.750	0.081
May	-1.312	0.485	-2.700	0.007	2000	2.651	0.899	2.950	0.003
June	-0.323	0.563	-0.570	0.567	2001	11.191	0.927	12.070	0.000
July	2.136	0.692	3.090	0.002	2002	0.997	0.910	1.100	0.273
August	0.550	0.137	4.010	0.000	2003	9.971	0.979	10.190	0.000
September	0.369	0.148	2.490	0.013	2004	20.192	1.021	19.780	0.000
Interaction of monthly rainfall and average maximum temp					2005	12.097	0.953	12.700	0.000
April	-0.095	0.007	-13.260	0.000	2006	11.969	1.081	11.070	0.000
May	0.007	0.007	1.090	0.274	2007	15.760	1.127	13.990	0.000
June	0.009	0.007	1.340	0.179	2008	7.038	1.124	6.260	0.000
July	-0.006	0.008	-0.770	0.441	2009	14.365	1.184	12.130	0.000
August	0.000	0.002	0.040	0.964	Time Variant endogenous				
September	-0.012	0.002	-6.060	0.000	Irrigated	31.584	0.334	94.630	0.000
Maximum monthly temperature					Early	1.453	0.246	5.910	0.000
April	1.186	0.051	23.120	0.000	Dummy variables for soil type with silt loam as base				
May	0.106	0.057	1.850	0.064	Clay	-14.457	0.485	-29.810	0.000
June	-0.672	0.057	-11.810	0.000	Silty clay loam	-2.218	0.218	-10.190	0.000
July	-0.021	0.062	-0.340	0.733	Clay loam	-3.940	0.327	-12.040	0.000
August	-1.719	0.056	-30.480	0.000	Loam	-8.589	0.298	-28.820	0.000
September	0.068	0.032	2.160	0.030	Sandy loam	-0.505	0.336	-1.500	0.133
Minimum monthly temperature					Sand	-10.765	0.604	-17.810	0.000
April	-0.598	0.058	-10.280	0.000	Time Invariant exogenous				
May	0.231	0.061	3.800	0.000	CB only	9.306	0.816	11.400	0.000
June	1.733	0.069	25.160	0.000	RW only	4.631	3.849	1.200	0.229
July	0.393	0.071	5.530	0.000	Ht only	1.981	1.291	1.530	0.125
August	-0.157	0.073	-2.140	0.033	CBHt	6.389	1.019	6.270	0.000
September	-0.430	0.043	-9.890	0.000	RW Ht	16.610	2.870	5.790	0.000
Dummy variables for state with Missouri as base					CB RW	15.015	2.898	5.180	0.000
IL	20.244	0.381	53.100	0.000	CB RW Ht	16.931	1.083	15.630	0.000
IN	15.881	0.476	33.330	0.000	Constant	96.078	5.784	16.610	0.000
IA	-4.494	0.437	-10.290	0.000					
KS	5.966	0.453	13.170	0.000					
MN	16.271	0.577	28.210	0.000					
MS	-27.612	0.732	-37.750	0.000					
NE	8.145	0.477	17.070	0.000					
OH	12.734	0.495	25.750	0.000					
SD	10.391	0.576	18.050	0.000					
WI	26.609	0.504	52.850	0.000					
Group variable	nid				Observations	211004			
Random effects u_i ~ i.i.d.		sigma_u	23.872		Number of groups	11731			
Wald chi ² (74)	89528.6	sigma_e	30.138		Observation per group	Minimum	5		
Prob > chi ²	0	rho	0.386			Average	18		
						Maximum	387		

for the time invariant regressors. The strong advantage of the Hausman Taylor approach is that there is no need to use external instruments.

We have re-estimated our model using the Hausman Taylor estimator, so that we have been able to identify the coefficients of the GM traits associated with each hybrid. The unobserved effects, α_i , are now net of the contribution of the GM traits, so that we have two measures of innovation: the first being the total contribution to yield of the genetic characteristics of the hybrid, and the second the contribution to yield by the hybrid net of the effects of its GM traits. We have also been able to identify the coefficients of the dummy variables for the GM traits.

Results

The results for both the fixed effects and Hausman Taylor models are highly significant, and those for the fixed effects model confirm that we should reject the null hypothesis that there is no correlation between the unobserved trial invariant effect, α_i , and the independent variables. The results of the fixed effects model can be found in Appendix 2. The results of the Hausman Taylor model are reported in table 5.

The coefficients for the observed independent variables in each model are essentially the same. There are some minor differences in magnitudes, but the signs and the levels of significance are consistent across both models. In order to estimate technical change, we have predicted the unobserved effect for each hybrid in each model. It should be recalled that this value is the amount by which the contribution of the characteristics of the individual hybrid are above or below the mean contribution of all hybrids. The change in the maximum unobserved effect for each year demonstrates the change in varietal contribution to yield. If we estimate the accumulated change, we can see the increase in contribution to yield of varietal

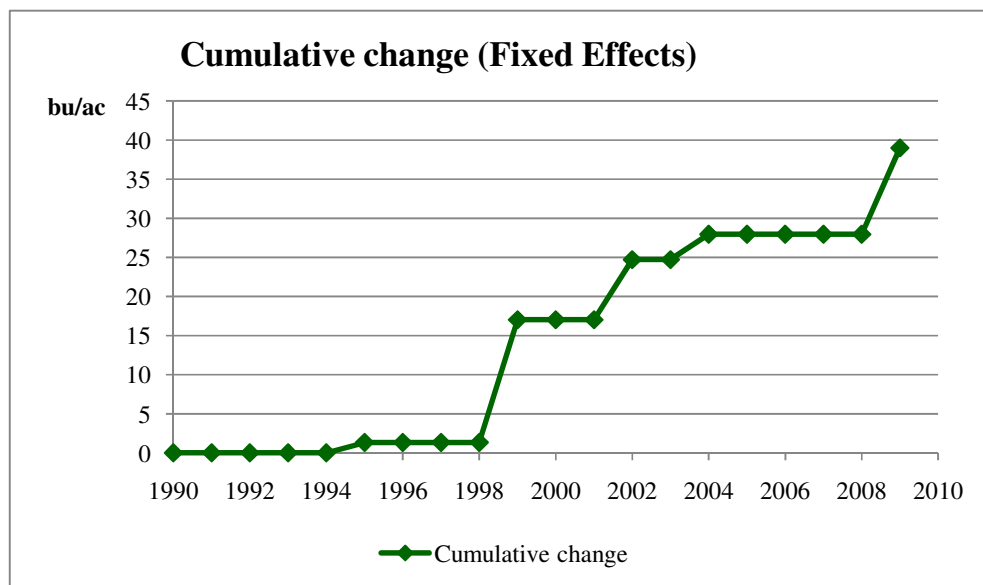


Figure 1a Cumulative change in genetic contribution of hybrids

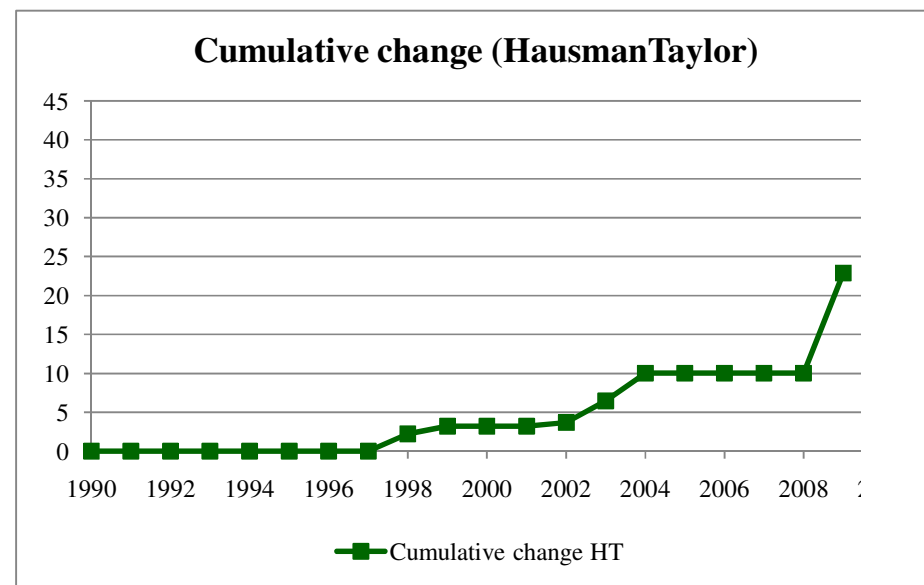


Figure 1b Cumulative change in genetic contribution of hybrids net of effect of GM traits

change. The charts in figure 1 show the accumulated growth in genetic contribution. Figure 1a shows the increase in contribution to output including the effect of the traits. There was clearly stagnation in the contribution of varietal characteristics in the early half of the 1990s. Contribution of varietal change to yield in bushels per acre started to increase in the mid 1990s. This was the point at which GM traits started to be tested in the university trials. In the late 1990s and the 2000s it is evident that the contribution of GM traits increases, but there is still an increase, albeit much smaller, in the contribution of the underlying hybrid as can be seen in figure 1b. The timing of the increases corresponds both with increased adoption of GM (in figure 1a) and with increased corn seed industry consolidation.

We have retained the fixed effects model because it provides a value for the total genetic contribution of each hybrid. The Hausman Taylor estimator allows us to identify the coefficients for individual GM traits and for stacked genes, and the unobserved effect for that model now provides a value for the genetic contribution of each hybrid *net* of the effect of the GM traits. The most interesting result is the identification of the contribution of each hybrid, but the Hausman Taylor estimator also allows us to identify the contribution of the individual traits.

In interpreting the effect of the GM traits it is important to recall that in this paper we are considering only the effect on yields in bushels per acre, without taking into account any cost saving qualities, for example, of the trait. It can be seen that the corn borer resistant trait has a positive coefficient and is significant at the 1 per cent level of significance. Neither corn rootworm resistance nor herbicide tolerance alone is significant at the 10 per cent level of significance. Corn borer resistance combined with herbicide tolerance is highly significant, but the combined effect is less than the effect for corn borer resistance alone. However, rootworm resistance combined with

either corn borer resistance or herbicide tolerance is strongly positive and is significant at the 1 per cent level of significance. The effect of all three categories of GM trait is greater when they are all combined, and the effect is much more strongly significant, with a z statistic of 15.63.

The maximum unobserved effect for 2009 requires some investigation. It relates to a non-GM variety tested in ten trials, but only in Ohio in 2009. It performed extremely well, but only in one state in one year. One of the limitations of our analysis so far is that it does not take into account the fact that hybrids are bred for particular conditions and particular locations. We are comparing all hybrids with the mean hybrid for the whole sample. The analysis could be improved by dividing the sample into regions, and estimating a model for each of the regions. While we could split the sample by state, the split would not necessarily correspond to agroecological zones. One means of approaching this problem is to recursively partition the dataset and to fit a multiple linear model to the observations in each partition using regression trees (see, for example, Loh (2010)).

Conclusion

We believe that the results of this study are relevant for the agricultural sector. There is increasing concern that the introduction of IPRs for plant breeding has led to a less than desirable level of concentration in the plant breeding industry. While these results do not allow us to reach any conclusions regarding the influence of IPRs and market concentration, they do provide a basis for further study. It is not possible to measure the effect of market concentration on innovation unless there is a reliable measure of innovation. We are not aware of any other work that has specifically identified the effect of varietal change on changes in yield, nor of work that has identified the effects of GM traits on changes in yield.

The results do not allow us to determine whether or not innovation, or lack of innovation, can be attributed to the introduction of IPRs, to consolidation in the industry or to the introduction of genetically modified hybrids. A comprehensive evaluation of the contribution of breeders to increasing yields requires more than an examination of the relative movement of average yields. As Brennan (1984) notes, such an evaluation would require an examination at farm level of the effect on farm production of changes in varieties grown by farmers; it needs to allow specifically for changes in amounts of other inputs used, and it should allow for differences in rates of increase of farm and experimental yields. The analysis also assumes that the contribution of varietal change will not vary between regions, and this is not realistic, as is demonstrated by our preliminary investigation through regression tree analysis. In further work we intend to divide the data into agroecological regions, and to repeat the analysis on a regional basis. An index of Total Factor Productivity could be introduced to account for changes in costs and methods of production.

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References

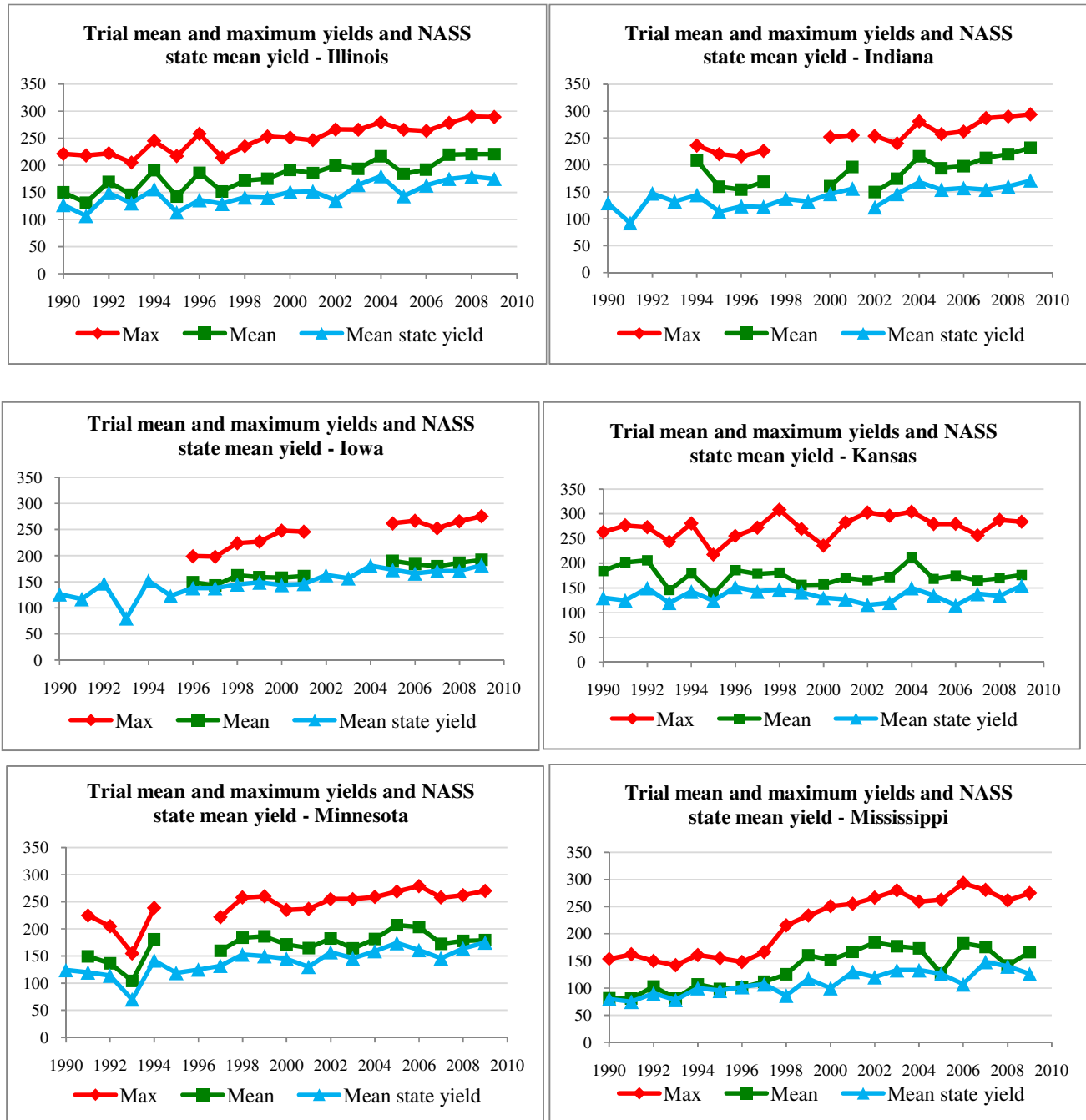
Alston, J., and R. Venner. 2002. The Effects of The US Plant Variety Protection Act on Wheat Genetic Improvement. *Research Policy* 31(4):527-542.

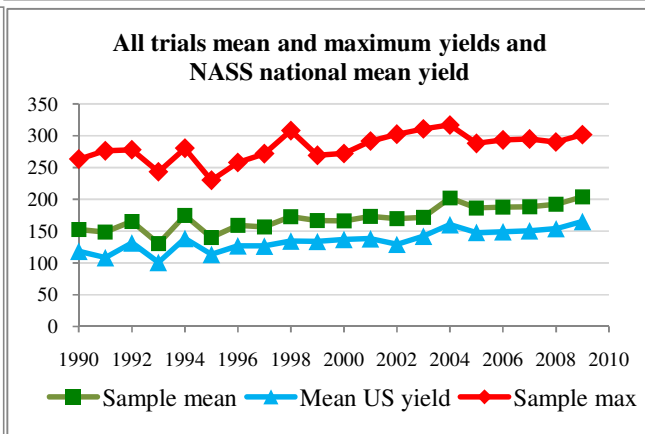
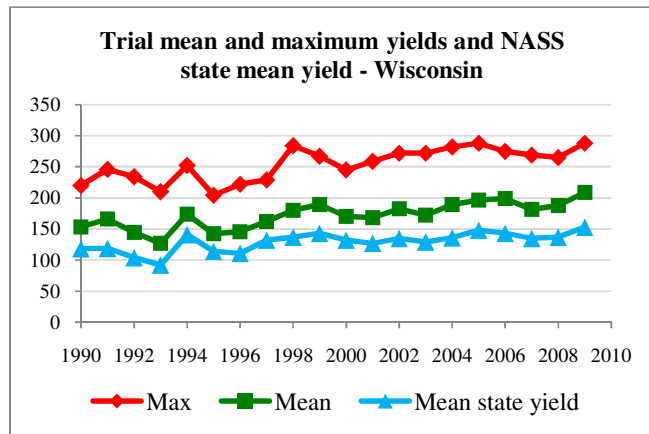
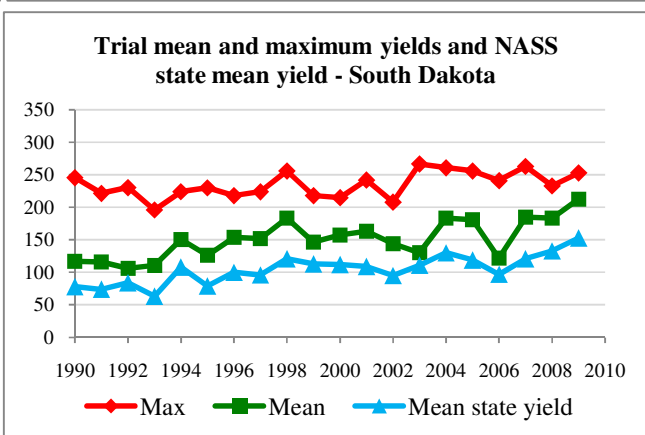
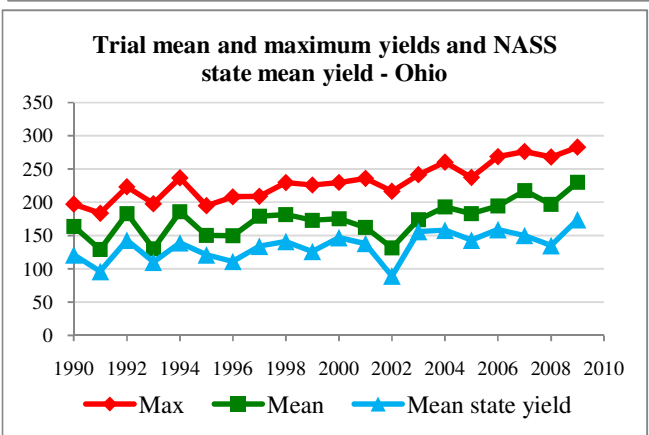
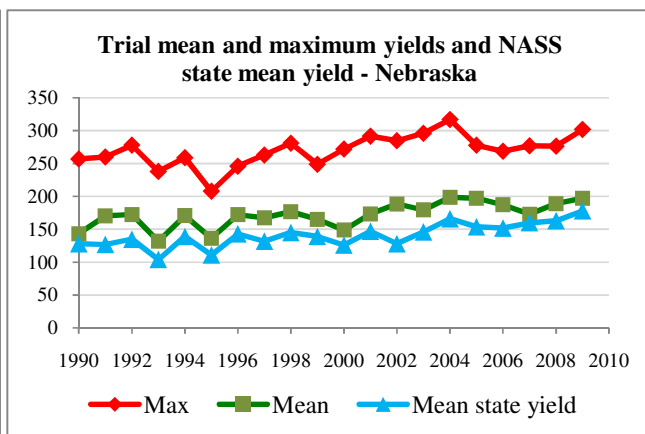
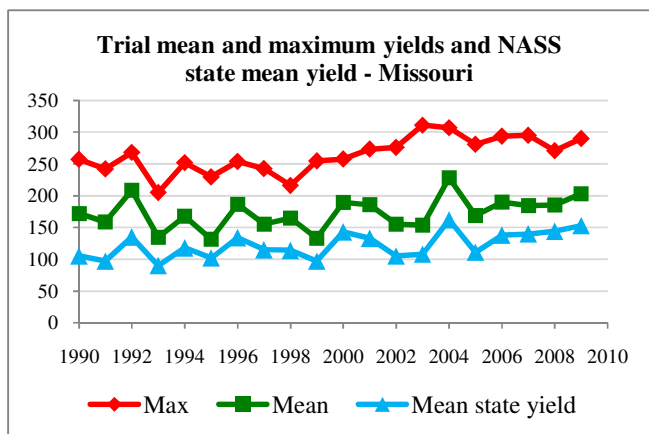
- Babcock, B. A., and W. E. Foster. 1991. Measuring the Potential Contribution of Plant Breeding to Crop Yields: Flue-Cured Tobacco, 1954-87. *American Journal of Agricultural Economics* 73(3):850-859.
- Brennan, J. P. 1984. Measuring the Contribution of New Varieties to Increasing Wheat Yields. *Review of Marketing and Agricultural Economics* 52(3):175-195.
- Brennan, M., C. Pray, A. Naseem, and J. Oehmke. 2005. An Innovation Market Approach to Analyzing Impacts of Mergers and Acquisitions in the Plant Biotechnology Industry. *AgBioForum* 8(2&3):89-99.
- Cameron, A. C., and P. Trivedi. 2010. *Microeconometrics Using Stata*. College Station, Texas: Stata Press.
- Chavas, J.-P., K. Kim, J. Lauer, R. Klemme, and W. Bland. 2001. An Economic Analysis of Corn Yield, Corn Profitability, and Risk at the Edge of the Corn Belt. *Journal of Agricultural and Resource Economics* 26(1):230-247.
- Department of Agronomy and Horticulture University of Nebraska- Lincoln. Corn Variety Test Results from UNL Extension. Available from URL: <http://cropwatch.unl.edu/web/varietytest/corn>. [Accessed on various dates in 2009 and 2010]
- Department of Agronomy Purdue University. Purdue Corn and Soybean Performance Trials. Available from URL: <http://www.ag.purdue.edu/agry/PCPP/Pages/corn.aspx>. [Accessed on various dates in 2009 and 2010]
- Department of Crop Sciences University of Illinois at Urbana-Champaign. Corn Hybrid Test Results in Illinois. Available from URL: <http://vt.cropsci.illinois.edu/>. [Accessed on various dates in 2009 and 2010]
- Division of Plant Sciences University of Missouri. Missouri Corn Performance Tests. Available from URL: <http://varietytesting.missouri.edu/corn/index.asp>. [Accessed on various dates in 2009 and 2010]
- Eisgruber, L. M., and L. S. Schuman. 1963. The Usefulness of Aggregated Data in the Analysis of Farm Income Variability and Resource Allocation. *Journal of Farm Economics* 45(3):587-591.
- Extension Agronomy Kansas State University. Kansas Performance Tests with Corn Hybrids. Available from URL: <http://www.agronomy.ksu.edu/extension/DesktopDefault.aspx?tabid=93>. [Accessed on various dates in 2009 and 2010]
- Fernandez-Cornejo, J., and D. Schimmelpfennig. 2004. Have Seed Industry Changes Affected Research Effort? *Amber Waves* 2(1)
- Gallini, N. 2002. The Economics of Patents: Lessons from Recent U.S. Patent Reform. *Journal of Economic Perspectives* 16(2):131-154.
- Geroski, P. 1994. *Market Structure, Corporate Performance and Innovative Activity*. Oxford: Clarendon Press.
- Graff, G. D., B. Wright, A. Bennett, and D. Zilberman. 2004. Access to Intellectual Property is a Major Obstacle to Developing Transgenic Horticultural Crops. *California Agriculture* 58(2):120-126.

- Greene, W. H. 2003. *Econometric Analysis*. Upper Saddle River, New Jersey: Prentice Hall.
- Griliches, Z., A. Pakes, and B. H. Hall. 1986. The Value of Patents as Indicators of Inventive Activity NBER Working Paper No. 2083, National Bureau of Economic Research. Available from URL: <http://ssrn.com/paper=228007>. [Accessed on 28 January 2010]
- Hausman, J. A., and W. Taylor. 1981. Panel Data and Unobservable Individual Effects. *Econometrica* 49(6):1377-1398.
- Heisey, P., and M. Morris 2002. Practical Challenges to Estimating the Benefits of Agricultural R&D: The Case of Plant Breeding Research. 2002 Annual Meeting of the American Agricultural Economics Association, Long Beach, California, 28-31 July 2002.
- Iowa Environmental Mesonet: Iowa State University Department of Agronomy. 2009. *IEM "Climodat" Reports*. Available from <http://mesonet.agron.iastate.edu/climodat/index.phtml>: [Accessed on various dates in 2009]
- Iowa State University Crop Testing. Iowa Crop Performance Test – Corn. Available from URL: <http://www.croptesting.iastate.edu/>. [Accessed on various years in 2009 and 2010]
- Kolady, D. E., and W. Lesser. 2009. But are they Meritorious? Genetic Productivity Gains under Plant Intellectual Property Rights. *Journal of Agricultural Economics* 60(1):62-79.
- Lanjouw, J. O., A. Pakes, and J. Putnam. 1998. How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data. *The Journal of Industrial Economics* 46(4):405-432.
- Loh, W.-L. 2010. User Manual for GUIDE 8. Department of Statistics, University of Wisconsin-Madison. Available from URL: <http://www.ers.usda.gov/Data/BiotechCrops/ExtentofAdoptionTable1.htm>. [Accessed on various dates in 2010]
- Mikel, M. A., and J. W. Dudley. 2006. Evolution of North American Dent Corn from Public to Proprietary Germplasm. *Crop Science* 46(3):1193-1205.
- Minnesota Agricultural Research Station University of Minnesota. Varietal Trials Results Corn Grain. Available from URL: <http://www.maes.umn.edu/vartrials/corn/index.asp>. [Accessed on various dates in 2009 and 2010]
- Mississippi State University Extension Service. Variety Test Results: Corn for Grain Hybrid Trials. Mississippi State University. Available from URL: <http://msucares.com/pubs/crops3.html#grain>. [Accessed on various dates in 2009 and 2010]
- Nalley, L., A. Barkley, and F. Chumley. 2008. The Impact of the Kansas Wheat Breeding Program on Wheat Yields, 1911-2006. *Journal of Agricultural and Applied Economics* 40(3):913-925.
- Naseem, A., J. Oehmke, and D. Schimmelpfennig. 2005. Does Plant Variety Intellectual Property Protection Improve Farm Productivity? Evidence from Cotton Varieties. *AgBioForum* 8(2&3):100-107.

- OARDC Ohio State University. 2009. *OARDC Weather System*. Available from URL: <http://www.oardc.ohio-state.edu/newweather/>. [Accessed on various dates in 2009]
- Ohio State University Extension. Ohio Corn Performance Test. Available from URL: <http://agcrops.osu.edu/~perf/>. [Accessed on various dates in 2009 and 2010]
- PRISM Climate Group Oregon State University. 2009. *PRISM Data Explorer*. Available from http://gisdev.nacse.org/prism/nn/index.phtml?vartype=ppt&month=04&year0=1971_2000&year1=1971_2000: [Accessed on Various dates in 2009 and 2010]
- Rausser, G., S. Scotchmer, and L. Simon. 1999. Intellectual Property and Market Structure in Agriculture Working Paper No. 880, Department of Agricultural and Resource Economics, University of California at Berkeley.
- Schimmelpfennig, D., C. Pray, and M. Brennan. 2004. The Impact of Seed Industry Concentration on Innovation: A Study of U.S. Biotech Market Leaders. SSRN. Available from URL: <http://ssrn.com/paper=365600>. [Accessed on 10 December 2008]
- South Dakota State University Cooperative Extension Service. Corn: Precision Planted Performance Trials. South Dakota State University. Available from URL: <http://plantsci.sdstate.edu/rowcrops/Corn/index.cfm>. [Accessed on various dates in 2009 and 2010]
- Traxler, G., J. Falck-Zepeda, J. I. Ortiz-Monasterio, and K. Sayre. 1995. Production Risk and the Evolution of Varietal Technology. *American Journal of Agricultural Economics* 77(1):1-7.
- University of Wisconsin Department of Agronomy. Wisconsin Corn Hybrid Performance Trial Results, University of Wisconsin. Available from URL: <http://corn.agronomy.wisc.edu/HT/Default.aspx>. [Accessed on various dates in 2009 and 2010]
- USDA National Agricultural Statistics Service (NASS). 2009. Adoption of Genetically Engineered Crops in the US: Corn Varieties. Available from URL: <http://www.ers.usda.gov/Data/BiotechCrops/ExtentofAdoptionTable1.htm>. [Accessed on various dates in 2009-2010]
- USDA Natural Resources Conservation Service. 2010. *Web Soil Survey*. Available from <http://websoilsurvey.nrcs.usda.gov/app/>: [Accessed on 22 January, 2010]
- Verbeek, M. 2009. *A Guide to Modern Econometrics*. Chichester: John Wiley and Sons.
- Wright, B., and P. Pardey. 2006. The Evolving Rights to Intellectual Property Protection in the Agricultural Biosciences. *International Journal of Technology and Globalisation* 2(1/2):93-114.

Appendix 1 University trial results compared with NASS average results by state





Appendix 2 Fixed-effects (within) Regression

	Coef.	Std. Err.	t	P> t		Coef.	Std. Err.	t	P> t
Seeding rate ('000)	2.745	0.000	84.220	0.000	Average minimum monthly temperature				
No or minimum till	-7.597	0.278	-27.350	0.000	April	-0.701	0.060	-11.770	0.000
Irrigated	31.431	0.338	93.010	0.000	May	0.220	0.062	3.530	0.000
Early	4.602	0.256	17.970	0.000	June	1.559	0.071	22.040	0.000
Previous crop (soybean as base)					July	0.403	0.073	5.520	0.000
Corn	-5.111	0.251	-20.360	0.000	August	-0.252	0.075	-3.360	0.001
Wheat	-2.411	0.329	-7.320	0.000	September	-0.395	0.044	-8.890	0.000
Alfalfa	4.976	0.603	8.260	0.000	Dummy variables for state with Missouri as base				
Other	-4.348	0.401	-10.840	0.000	IL	20.027	0.394	50.800	0.000
Dummy variables for soil type with silt loam as base					IN	14.399	0.496	29.030	0.000
Clay	-14.372	0.490	-29.310	0.000	IA	-5.042	0.450	-11.200	0.000
Silty clay loam	-2.141	0.220	-9.720	0.000	KS	5.527	0.465	11.900	0.000
Clay loam	-2.757	0.332	-8.310	0.000	MN	19.435	0.598	32.490	0.000
Loam	-7.658	0.302	-25.360	0.000	MS	-29.779	0.789	-37.740	0.000
Sandy loam	0.738	0.341	2.170	0.030	NE	6.918	0.490	14.110	0.000
Sand	-10.739	0.611	-17.560	0.000	OH	10.762	0.517	20.830	0.000
Monthly rainfall					SD	11.183	0.594	18.830	0.000
April	4.033	0.463	8.710	0.000	WI	30.591	0.524	58.330	0.000
May	-1.867	0.497	-3.760	0.000	Dummy variables for year with 1990 as base				
June	-0.846	0.574	-1.470	0.140	1991	-5.511	0.755	-7.300	0.000
July	1.643	0.704	2.340	0.020	1992	-2.168	0.854	-2.540	0.011
August	0.546	0.139	3.940	0.000	1993	-33.103	0.908	-36.470	0.000
September	0.388	0.150	2.590	0.010	1994	8.911	0.851	10.470	0.000
Interaction of monthly rainfall and average maximum temp					1995	-12.562	0.995	-12.620	0.000
April	-0.079	0.007	-10.880	0.000	1996	-2.779	0.900	-3.090	0.002
May	0.015	0.007	2.230	0.026	1997	-7.006	0.931	-7.520	0.000
June	0.015	0.007	2.150	0.032	1998	11.224	1.062	10.570	0.000
July	-0.001	0.008	-0.120	0.901	1999	-3.656	1.100	-3.320	0.001
August	-0.001	0.002	-0.390	0.695	2000	-3.893	1.083	-3.600	0.000
September	-0.012	0.002	-5.840	0.000	2001	4.058	1.131	3.590	0.000
Average maximum monthly temperature					2002	-6.518	1.136	-5.740	0.000
April	1.012	0.053	19.260	0.000	2003	0.099	1.217	0.080	0.935
May	0.123	0.059	2.100	0.036	2004	8.733	1.277	6.840	0.000
June	-0.761	0.058	-13.100	0.000	2005	2.113	1.240	1.700	0.088
July	0.032	0.063	0.510	0.608	2006	0.133	1.373	0.100	0.923
August	-1.771	0.058	-30.630	0.000	2007	2.489	1.442	1.730	0.084
September	-0.016	0.032	-0.500	0.616	2008	-7.939	1.469	-5.400	0.000
					2009	-0.900	1.535	-0.590	0.558
					_cons	152.613	5.936	25.710	0.000
Group variable	nid				Number of obs	211004	Obs per group:	Minimum	5
F(67,199206)	1239.490				Number of groups	11731		Average	18
Prob > F	0.000							Maximum	387
corr(u_i, Xb)	-0.116				R-sq:	Within	0.294		
F test that all u_i=0:						Between	0.211		
F(11730, 199206)	3.730					Overall	0.262		
Prob > F	0.000								

Appendix 3 Correlation Matrix for IVs for Hausman Taylor Estimator

	Irrigated	Early	Clay	Silty clay loam	Clay loam	Loam	Sandy loam	Sand	CB	RW	Ht	CBHt	RWHt	CBRW	CBRWHt	Hybrid effect
Irrigated	1.000															
Early	-0.115	1.000														
Clay	-0.033	0.020	1.000													
Silty clay loam	-0.169	-0.066	-0.076	1.000												
Clay loam	-0.113	0.093	-0.042	-0.123	1.000											
Loam	-0.057	0.074	-0.046	-0.137	-0.075	1.000										
Sandy loam	0.217	0.085	-0.039	-0.114	-0.063	-0.070	1.000									
Sand	0.245	0.075	-0.021	-0.062	-0.034	-0.038	-0.032	1.000								
CB	0.011	-0.040	-0.018	0.017	-0.016	-0.006	-0.020	0.010	1.000							
RW	-0.010	-0.002	-0.002	0.008	-0.007	-0.004	0.000	-0.005	-0.020	1.000						
Ht	0.000	0.080	0.022	0.009	0.013	0.010	0.011	0.008	-0.078	-0.009	1.000					
CBHt	0.026	0.069	0.004	0.003	0.015	0.021	0.011	0.011	-0.132	-0.014	-0.056	1.000				
RWHt	-0.014	0.003	-0.006	0.022	-0.008	0.004	-0.010	-0.003	-0.037	-0.004	-0.016	-0.026	1.000			
CBRW	-0.009	-0.003	-0.001	0.011	-0.007	0.010	-0.006	-0.004	-0.033	-0.004	-0.014	-0.023	-0.006	1.000		
CBRWHt	-0.034	0.054	0.002	0.053	0.007	0.045	-0.023	-0.010	-0.167	-0.018	-0.071	-0.119	-0.033	-0.030	1.000	
Hybrid effect	0.076	-0.362	0.057	0.099	-0.160	-0.040	-0.139	-0.077	-0.040	-0.004	0.005	0.006	0.004	-0.007	0.008	1.000