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Intellectual Property Rights, Technology Diffusion, and Agricultural Development

Cross-Country Evidence

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ABSTRACT

The role of intellectual property rights (IPRs) has been extensively debated in the literature on technology transfers and agricultural production in developing countries. However, few studies offer cross-country evidence on how IPRs affect yield growth, for example, by incentivizing private-sector investment in cultivar improvement. We address this knowledge gap by testing technology diffusion patterns for six major crops using a unique dataset for the period 1961–2010 and an Arellano–Bond linear dynamic panel-data estimation approach. Findings indicate that both biological and legal forms of IPRs tend to promote yield gap convergence between developed and developing countries, although effects vary between crops.

Keywords: technology transfers, intellectual property rights, agricultural productivity growth, agricultural development, developing countries

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1. INTRODUCTION

The expansive literature on agricultural development provides rich grounding for the argument that technological change is a key driver of agricultural development, economic growth, and poverty reduction (Johnston and Mellor 1961; Schultz 1968; Hayami and Ruttan 1971; Binswanger and von Braun 1991). The empirical evidence largely supports this argument (for example, Fan and Pardey 1997; Fan 2000; Fan, Hazell, and Thorat 2000). There is also rich grounding for the argument that economic policy incentives encourage investment in agricultural research and development (R&D) that underpins technological change (Evenson and Kislerv 1973; Alston, Norton, and Pardey 1995; Alston, Pardey, and Smith 1999) and technology adoption by farmers (Feder et al. 1985; Lipton and Longhurst 1989). This is particularly relevant to cultivar improvement for major food staple crops which, according to estimates from Evenson and Gollin (2003), account for 20–50 percent of yield growth trends in developing countries between 1960 and 2000.

However, the study of innovation incentives in developing-country agriculture since the 1970s has focused primarily on the contribution of public research and extension systems (see, for example, Alston et al. 2000). Only in the last two decades have incentives for private investment in the research, development, and delivery of new agricultural technologies become a topic of significant discussion (Naseem, Spielman, and Omamo 2010). This follows not only from the successful commercialization of emerging scientific advances (for example, genetic modification, genomics, and informatics) led by the private sector, but also from the slow growth in public R&D expenditures and limited scientific output from public research organizations in many low-income developing countries (Pray 1992; Pardey and Beintema 2001; Byerlee, Alex, and Echeverría 2002; Beintema et al. 2012). As a result, many scholars predict greater reliance on private R&D investment in developing-country agriculture and thus on private R&D incentives such as intellectual property rights (IPRs) (Byerlee and Fischer 2002; Pingali and Traxler 2002; Spielman 2007).

In broad terms, theory suggests that when IPRs enable developed-country innovators to profitably transfer technologies to developing countries—and when developing-country innovators can imitate, adapt, and improve these innovations at a lower cost—then IPRs can contribute to technological change, economic growth, and welfare improvement in the developing world. There is much conceptual and empirical evidence supporting this argument (Taylor 1993, 1994; Lai 1998; Lesser 2000; Kanwar and Evenson 2003), but also a significant body of theory and evidence that reveals its complex nuances (Chin and Grossman 1990; Deardorff 1992; Helpman 1993).

This argument over IPRs also extends to the agricultural sector. IPRs can potentially encourage private investment in the development of new cultivars, genetically modified crops, livestock vaccines, crop protection chemicals, and other inputs that in turn can enhance agricultural productivity and foster agricultural development and poverty reduction (Lipton 1989; Pray 1992; Lesser et al. 2000; Eaton et al. 2006). However, IPRs can also provide private firms with temporary monopolies of a welfare-reducing nature that may limit small-scale, resource-poor farmers' access to technological solutions that increase on-farm productivity, improve household food security, and reduce poverty (Goeschl and Swanson 2000; Srinivasan and Thirtle 2000). It is also possible that IPRs simply do not matter to developing-country agriculture because firms in developed countries rarely seek IPR protection for their technologies in developing countries, thus providing developing-country researchers and farmers with unimpeded freedom to operate (Binenbaum et al. 2003).

Empirical evidence on the contribution of IPRs to agricultural productivity growth is mixed. Several studies suggest that the US Plant Variety Protection Act of 1970 generated positive effects on cotton and wheat yield growth rates (Perrin, Kunnings, and Ihnen 1983; Naseem, Oehmke, and Schimmelpfennig 2005; Kolady and Lesser 2009), although confounding evidence is also found for wheat and tobacco yields (Babcock and Foster 1991; Alston and Venner 2000). There is similarly positive evidence for canola and wheat yields from Canada's Plant Breeders Rights Act of 1990 (Carew and

Devadoss 2003; Carew, Smith, and Grant 2009). For developing-country agriculture, the evidence is similarly ambiguous (Naseem, Spielman, and Omamo 2010).

This paper addresses these issues by exploring the extent to which IPRs promote yield growth by encouraging the transfer of productivity-enhancing technologies from developed to developing countries. The paper extends the work of Goeschl and Swanson (2000), which examines how strong forms of IPR protection constrain productivity-enhancing technology diffusion from developed to developing countries. Their study, based on cross-country data from 1961 to 1991 for eight widely cultivated crops, indicates not only significant convergence in yield growth rates between developed and developing countries (“yield gap convergence”) but also significant impediments to convergence that are attributable to country-specific structural characteristics or crop-specific technological characteristics. The impediments associated with country-specific characteristics are readily explained by fundamental differences in agroecological, historical, political, and geographic features between countries (see, for example, Fulginiti, Perrin, and Yu 2004). Impediments associated with crop-specific characteristics, however, are mainly attributed by Goeschl and Swanson (2000) to economic incentives associated with the nature of the reproductive biology of individual crops. In particular, they attribute slower rates of yield gap convergence to hybridization, a biological phenomenon explained in detail later.

What the Goeschl and Swanson (2000) study lacks, however, is a treatment of other, more institutional constraints to yield gaps convergence. Specifically, their study does not fully address the role of *legal* forms of IPRs such as plant variety protection laws and enforcement of those laws, or other public policies designed to encourage technology transfers and commercial activity in the area of cultivar improvement. Thus, this paper provides a more complete exploration of both biological *and* legal IPRs across a large set of developing countries using a model that decomposes crop-specific movements toward yield gap convergence.

The paper proceeds as follows: Section 2 provides a conceptual discussion that ties together technology diffusion, private-sector innovation incentives, and agricultural productivity growth in developing countries. Section 3 sets forth an empirical specification, followed by details on data and data sources in Section 4. Results are discussed in Section 5, followed by concluding remarks in Section 6.

2. A CONCEPTUAL MODEL OF TECHNOLOGY DIFFUSION AND PRIVATE-SECTOR INCENTIVES

Studies of the impact of technology transfers on growth generally account for two key conditions: the ability of innovators to transfer their innovative products across countries, and the ability of innovators to appropriate a portion of the rents accruing from the use of those products. These conditions are neatly captured in a “follow-the-leader” model of economic growth originally proposed by Barro and Sala-i-Martin (1995), which posits that the growth rate of a follower country tends to catch up to that of a leader country because followers can imitate innovations produced by leaders at a lower cost. As a result of this catching-up process, followers and leaders tend to converge at the same steady-state rate of growth in the long term. In the context of developing-country agriculture, the underlying intuition of this model—the underlying dynamics of innovation, imitation, and technology transfers—is similarly applicable to the transfer of yield-enhancing technologies from developed countries that can be imitated by developing countries through adaptive research. The transfer of technologies such as improved cultivars is hypothesized to encourage the convergence of yield growth rates between developed and developing countries. This is the logic that underlies the Goeschl and Swanson (2000) model.

Necessarily, there are limitations to extending a macroeconomic growth model to a crop-specific yield growth model. First, the underlying assumptions of agent behavior are not perfectly analogous. Barro and Sala-i-Martin (1995) assume that growth is a function of intertemporal decisions made by rational profit-maximizing firms and utility-maximizing consumers. While the yield growth model makes a similar assumption about developing-country firms that adapt technologies transferred from developed countries, consumers in this model are represented by farmers who maximize profits, an economic variable, but not necessarily yields, an agronomic variable. Second, yield growth rates cannot be readily interpreted as a complete measure of agricultural productivity growth because they capture only land productivity (Headey, Alauddin, and Rao 2010). Measures of total factor productivity are better at capturing growth that is attributable to greater allocative or technical efficiency achieved through improvements in the way factors are combined in production (Coelli, Rao, and Battese 1998; Nin et al. 2003; Fuglie 2012). Third, yield data are subject to sampling and measurement error, particularly for earlier decades before systematic collection of such data began under the auspices of the Food and Agriculture Organization of the United Nations (FAO) (Goeschl and Swanson 2000). Fourth, the idea that yields should converge over time between countries has no theoretical foundation (Sumberg 2012).

Despite these limitations, yield growth rates can provide some insight into agricultural development more generally. For example, yield growth rates can be useful when analyzing the impact of food security policies—including policies on IPRs and technology transfers—on rural households in developing countries where yields may be correlated with measures of household consumption, poverty, and vulnerability. They can be useful in capturing the combined (and often indistinguishable) effects of changes in allocative efficiency, technical efficiency, and input intensification. They can also be useful when total factor productivity data are less complete in terms of countries or time periods, or when the questions of interest are specific to a particular crop or farming system. They can also be useful in indicating movements toward convergence, which themselves indicate some catching-up effect, even if yields themselves never converge.

Further, it is worth noting that Evenson and Kislev (1973) argue that where agricultural production functions are very elastic with respect to factor input substitution—where there is a high degree of complementarity between inputs—then the state of technology largely determines the factor input mix (Goeschl and Swanson 2000). This may be a reasonable assumption to make with respect to developing-country agriculture in the context of our inquiry.

It is this state of technology that we turn our attention to next in developing our conceptual model. We begin with the hypothesis that impediments to yield gap convergence associated with crop-specific characteristics hinge on the economic incentives that result from differences in the reproductive biology of individual crops. Specifically, Goeschl and Swanson (2000) distinguish between hybrid crops,

on the one hand, and open or self-pollinating crops, on the other hand, in explaining yield growth convergence. Hybrid crops are characterized by their unique ability to exhibit heterosis, or an increase in yield, uniformity, or vigor that results from genetic contributions derived from the crossing of distinct parental lines. The economic value of hybrids lies in the fact that yield gains conferred by heterosis decline dramatically after the first generation of seed, thus compelling farmers to purchase new seed each season and thus providing innovators with a means of appropriating the gains from their R&D investment. This attribute contrasts with open or self-pollinated crops, for which harvested grains can be stored and used as seeds in the following year without significant loss of vigor and without remuneration to the innovator. Findings from Goeschl and Swanson (2000) suggest that that yield enhancements embodied in hybrid crops diffuse less rapidly than enhancements embodied in open or self-pollinating crops, implying that the *biological* IPRs conferred by hybridization to developed-country innovators make it prohibitively costly for innovators in developing countries to imitate these technologies and for resource-poor farmers to purchase their embodiments in the form of hybrid seed.¹

In fact, there is much empirical evidence to show that technology flows for hybrid crops have contributed significantly to yield growth in developing countries, for example, for maize in Kenya, Malawi, Zambia, and Zimbabwe (Smale and Jayne 2010); pearl millet and sorghum in India (Pray and Nagarajan 2010; Gruere and Sun 2012); rice in China (Li, Xin, and Yuan 2010); and maize throughout Asia (Gerpacio 2003). However, in all cases, the introduction of hybrids was accompanied by some policy or institutional change that created some related economic incentives for private firms to develop and market hybrids. These changes include public policies that encourage commercial activity in the country's seed sector, or *legal* forms of IPRs such as plant variety protection certificates. For example, the contribution of hybrids to yield growth in India mentioned above was largely contingent on policy reforms that began in the late 1980s and encouraged international technology flows, private-sector innovation, and private investment in the seed industry (Pray 1992; Ramaswami 2002; Kolady, Spielman, and Cavalieri 2012). This suggests that policy reforms and legal IPRs can provide innovators with a means of appropriating the gains from their R&D investment in a manner similar to biological IPRs, and can thus affect the costs of technology facing both innovators and farmers in developing countries.

Necessarily, there are other possible explanations for yield growth apart from technology transfers resulting from improvements in innovation incentives and biological and legal IPRs. On the supply side, transfers of nonappropriable, public-goods knowledge such as new practices for managing crops, water, and soil nutrients may contribute to yield growth. On the demand side, growth in domestic and export market size and market value may similarly encourage farmers to invest in yield improvement. But even in the presence of such effects, the extent to which whether IPRs affect yield growth—and movements toward yield growth convergence between developed and developing countries—remains an interesting empirical question.

¹By extension, their study suggests that biological IPR mechanisms under development, for example, genetic-use restriction technologies, advanced hybridization systems, and other mechanisms based on crop reproductive biology designed to lower the cost of appropriating the gains from R&D, could impede future transfer of yield-enhancing technologies to developing countries (see also Goeschl and Swanson 2003a,b).

3. AN EMPIRICAL MODEL

To test whether IPRs influence the rate of yield gap convergence between developing and developed countries for a given crop, we specify the empirical model as follows:

$$G_{it} = c_i + \beta G_{i,t-1} + \gamma_1 \Delta MKT_{it} + \gamma_2 \Delta Area_{it} + \theta_1 \Delta IPR_{i,t} + \theta_2 \Delta IPR_{i,t-1} + \theta_3 \Delta IPR_{i,t-2} + \varepsilon_{it} \quad (1)$$

where G_{it} denotes the gap in yield growth rates between the leader country and the follower country i at time t for the given crop (Appendix A). The term G_{it} can be more accurately defined as

$$G_{it} = \frac{Y_t^* - Y_{t-1}^*}{Y_{t-1}^*} - \frac{Y_{it} - Y_{i,t-1}}{Y_{i,t-1}} = \frac{Y_t^*}{Y_{t-1}^*} - \frac{Y_{it}}{Y_{i,t-1}}, \quad (2)$$

where Y_{it} is the yield of country i in time t , and Y_t^* is the yield in the leader country in the same time period. We assume that the yield growth rate in the leader country is faster and therefore the gap is likely to be a positive number.

In Equation (1), the intercept term c_i captures country-specific, time-invariant structural factors in follower country i , for example, agroclimatic conditions, geographic distance from the leader country, traditional crop-management practices, or other factors that uniquely contribute to the yield gap between the leader country and the follower country. The coefficient β captures the overall rate of technology diffusion between the leader and follower countries across time, effectively measuring the magnitude by which the yield gap in the current time period responds to a change in the yield gap in the previous period.

The coefficient γ_1 denotes the effect on yields gaps associated with the growth rate of the i^{th} country's agricultural market size (ΔMKT_{it}). The underlying assumption is that a significant portion of the crop is used domestically for consumption or industrial purposes; therefore, the change of the agricultural market size may affect the yield growth in a developing country. This is likely to be true with respect to the food staple crops and the countries estimated for this model. Note that because market size and crop yields may be endogenously determined, we introduce population growth rate as a proxy variable for the agricultural market size, following Galushko and Gray (2012). The coefficient γ_2 denotes the effect on yield gaps associated with the rate of extensification, or a change in cultivated area ($\Delta Area_{it}$), in country i . It is based on the standard assumption that an expansion of cultivated area in a given country tends to push crop production into increasingly marginal land, and it is thus associated with a decrease in the yield growth rate.

The coefficient θ_l denotes the effect of changes in country i 's IPR regime strength (ΔIPR_{it}) at time t on yield gap convergence. We introduce a two-period lag effect (denoted $\Delta IPR_{i,t-1}$ and $\Delta IPR_{i,t-2}$) to capture the time required for a change of IPR regime to take effect in a given country and incentivize changes in firm behavior. Each lag period represents a 5-year increment, so the empirical model captures the IPR regime change effects in the current time period, after 5 years, and after 10 years. These lags are consistent with plant-breeding timelines ranging from fast-tracked importation of broadly adapted varieties that can be released quickly in a given country, to slower processes that require investments in adaptive breeding and regulatory testing (McMullen 1987; Gisselquist and Srivastava 1997; Gisselquist and Grether 2000).

Decomposition of Factors Affecting Yield Gap Convergence

Equation (1) allows for decomposition of changes in the yield gap for a given crop in country i into four distinct components—technological, production, institutional, and structural—based on the notion that each component affects the flow of yield-enhancing technologies from leader countries to follower countries.

The *technological component* refers to productivity-enhancing effects associated with the transfer of agricultural technologies that originate in developed countries and move to developing countries. By allowing y to denote the log value of yield Y , we can rearrange the yield gap term and express it more intuitively as $G_{it} = \Delta y_t^* - \Delta y_{it}$, where Δ signifies the change in the yield growth rate.² Assuming a positive initial yield gap, relative yield gains in country i are, over time, represented by a *decrease* in the gap toward convergence. Rearranging Equation (1) algebraically obtains

$$\Delta y_{it} = \Delta y_t^* - c_i - \beta G_{i,t-1} - \gamma_1 \Delta MKT_{it} - \gamma_2 \Delta Area_{it} - \theta_1 \Delta IPR_{it} - \theta_2 \Delta IPR_{i,t-1} - \theta_3 \Delta IPR_{i,t-2} - \varepsilon_{it}, \quad (3)$$

which states that yield gains in country i (Δy_{it}) are determined by yield gains occurring in the leader country (Δy_t^*); time-invariant, country-specific characteristics of the follower country (c_i); constraints associated with a crop-specific technology effect ($G_{i,t-1}$) and country-specific growth effects associated with agricultural production ($\Delta MKT_{it}, \Delta Area_{it}$); and changes in the IPR regime strength (ΔIPR_{it}). Table 3.1 summarizes the expected coefficient signs and their interpretations.

Table 3.1 Interpretation of coefficient estimates

Coefficient	Sign and magnitude	Interpretation
c_i	$c_i > 0$	Agroecology is unfavorable to yield gap convergence.
c_i	$c_i < 0$	Agroecologic conditions are favorable to yield gap convergence.
β	$-1 < \beta < 1$	Yield gap convergence where a smaller absolute value indicates a more rapid convergence rate.
β	$1 < \beta < -1$	Yield gap divergence.
γ_1	$\gamma_1 < 0$	An increase of agricultural market size increases yield gap convergence.
γ_1	$\gamma_1 \geq 0$	An increase of agricultural market size decreases yield gap convergence.
γ_2	$\gamma_2 < 0$	An increase of harvested area increases yield gap convergence.
γ_2	$\gamma_2 \geq 0$	An increase of harvested area decreases yield gap convergence.
$\theta_1, \theta_2, \theta_3$	$\theta_1, \theta_2, \theta_3 > 0$	Legal IPRs constrain imitation.
$\theta_1, \theta_2, \theta_3$	$\theta_1, \theta_2, \theta_3 < 0$	Legal IPRs incentivize imitation.
$\theta_1, \theta_2, \theta_3$	$\theta_1, \theta_2, \theta_3 = 0$	Legal IPRs have no effect on imitation.

Source: Authors' own definition.

²Diagnostic tests are passed in the estimation for all crops, as follows. The Arellano-Bond autoregressive test for order 2 in all our model specifications does not reject the null hypothesis of no autocorrelation for at least a 5 percent level of significance. The standard Hansen test and the difference-in-Hansen J tests for GMM estimation also show that our choice of instruments, that is, the further lags of yield gaps, as a group, are exogenous.

The relationship between technological innovation and relative yield gains enters Equation (1) through two separate terms: yield growth in the leader country (Δy_t^*) and the gap between the leader and the follower countries ($G_{i,t-1}$). The first term represents an exogenous, yield-enhancing change in the technological state at the “frontier” for a given crop that potentially carries over to all follower countries. The second term captures the diffusion of yield gains from the frontier to followers. The extent and rate at which diffusion occurs is captured by β . In this context, β is an estimate of the constraint imposed on diffusion and reflects the fact that technologies do not necessarily diffuse from the frontier to follower countries unimpeded because of certain characteristics of the crop and the technologies associated with cultivation.

The sign and magnitude of coefficient β are essential elements of this model and can be explained as follows. First, to demonstrate that developing countries are converging to the yield growth rate of the leader country, the diffusion rate β must satisfy the condition $|\beta| < 1$. Second, the closer the absolute value of β is to 1, the faster the diffusion rate. Third, if the absolute value of β is greater than 1, then yield growth rates in follower countries are falling behind those of the leader country. Fourth, if the (nonabsolute) value of β is negative, then yield growth rates in follower countries are catching up rapidly, such that yield growth rates may actually exceed those of the leader country on occasion, thereby accelerating the convergence process.

Figure 3.1 simulates the different convergence trajectories with different values of β . Assuming a constant growth rate of 1 percent in the leader country and an initial gap of 0.8 percent, the left-hand figure shows the trajectories when β is positive and the right-hand figure shows the trajectories when β is negative. For $|\beta| = 0.1, 0.5, 0.8$, all the trajectories show convergence after certain time periods, but follower countries catch up fastest when the absolute value of β is smallest, for example, when $|\beta| = 0.1$.

The *production component* refers to the productivity-enhancing effects of a growth in demand for agricultural commodities in the follower country or the productivity-depressing effects when crop production expands to inferior land. This effect is captured by a term measuring annual agricultural market growth for follower i and a term measuring the change of harvested area. The coefficient γ_1 reflects the responsiveness of the yield gap to agricultural-sector growth in country i . Intuitively, positive agricultural market growth in country i is associated with an increase in the demand for yield-enhancing technologies imitated from the leader country, resulting in gap-reducing yield growth. If so, then γ_1 is expected to assume a value of less than zero. It is also possible for the yield gap in country i to remain unresponsive to agricultural-sector growth, as when yield-enhancing technologies exist at the frontier but sectoral conditions in country i offer insufficient demand or profitability incentives for private agents to transfer or disseminate technology. Relatedly, the sign of γ_2 is likely to be positive if extensification results in cultivation of increasingly marginal land.

Figure 3.1 Simulations of crop yield convergence rates

Source: Authors' own simulation.

Note: Assuming a constant growth rate for the leader country and an initial yield gap of 0.8 for the follower country.

The *institutional component* refers to the productivity-enhancing effects of an institutional (that is, policy) regime that encourages innovation. This effect is captured by a term measuring changes in the IPR regime strength for follower country i . The degree to which changes in the IPR regime of country i encourage or impede yield enhancement, measured by a change in the yield gap, is reflected by the coefficient θ . A coefficient θ that is greater than zero implies that an increase in IPR regime strength is associated with an increase in the yield gap. This may be interpreted as an institutional barrier to yield-enhancing technological diffusion. A coefficient θ less than zero implies that an increase in IPR regime strength is associated with a decrease in the yield gap, or an institutional incentive to yield-enhancing technological diffusion. Alternatively, the coefficient may be interpreted as the extent to which an IPR regime signals innovators that rents from their innovations are appropriable in country i .

The *agroecological component* captures other conditions in country i that affect the success of yield-enhancing technologies imitated by the follower country; it is represented by the time-invariant, country-specific intercept term c_i (explained earlier). In addition to agroecological differences between countries, this component may also capture certain institutional factors, for example, rural education systems, historical path dependencies, and political regimes.

Estimation

Because the lagged dependent variable $G_{i,t-1}$ appears in Equation (1) as an explanatory variable, the estimation model violates the strict exogeneity assumption; that is, the idiosyncratic error in the current time period will be correlated with the explanatory variables in the past. It is thus impossible to apply the standard random- or fixed-effects panel data estimation techniques that rely on this assumption to estimate a model with an unobserved individual effect (Wooldridge 2010). This also rules out the possibility of ordinary least squares estimation. To remedy this, we apply a linear dynamic panel data estimation developed by Arellano and Bond (1991) (Appendix B). The Arellano–Bond model uses a generalized method of moments (GMM) framework by using further lagged values of the explanatory variables as instruments and resolves the correlation of the idiosyncratic error by using an efficient weighting matrix, therefore yielding consistent and efficient estimators (Wooldridge 2010).

We estimate a country fixed-effects specification of the Arellano–Bond model with a balanced panel of cross-country data for the period 1961–2010. The fixed-effects estimation cancels out the time-invariant, country-specific intercept term c_i while generating estimates for all other coefficients. Considering that some crops in our data are not produced in many countries, we restrict the number of lags to be used as instruments.

4. DATA AND DATA SOURCES

Data on crop yields are taken from the FAO's online database (FAOSTAT) for the period 1961–2010 for a set of major food crops (FAO 2013). Yield gaps for each crop are calculated as the difference between the yield growth rate for crop n in developing country i in time period t and the yield growth rate in the leader country for the same crop and the same time period. Across the period 1961–2010, this yield gap variable is generally greater than zero, indicating a decreasing level of yield inferiority (that is, an increasing movement toward yield gap convergence) between developing and leader countries (Figure 4.1).

Figure 4.1 Crop yields in leader and follower countries, 1961–2010 (log hg/ha)

Source: FAOSTAT (2013).

Note: hg = hectogram; ha = hectare. The upper, solid line shows the crop yield in the leader country in 1961–2010. The lower, dashed line shows the average crop yield among follower countries in our sample in 1961–2010.

The *leader country* is a composite of countries reporting the highest yields for each crop based on data from FAO (2013) (Table 4.1). Some countries included in the composite are easily recognizable as global leaders in production and R&D for the specific crop, for example, the United States with respect to cotton; however, other countries are not, for example, Egypt with respect to rice. To the extent possible, we omitted the most obvious outliers (for example, the Democratic People's Republic of Korea with respect to millet), but resort to a set selection rule for designating the country leader. Specifically, we define the leader country as a fixed group of five countries that report the highest average annual yields between 1961 and 2010 (Table 4.1). We then use the average yields in five-year increments from all five countries to calculate the yield gap. This allows for calculation of a credible leader-country variable while minimizing any effects caused by single-country idiosyncrasies in the yield data. However, the selection rule does not necessarily remove less-than-credible artifices in the FAO data that are evident in Table 4.1. Sensitivity analysis using alternative compositions of the leader country (discussed later) are inconsequential to our estimations.

Table 4.1 Crops, yields, yield gaps, and leader countries

Crop	Average yield in leader countries (hg/ha)	Average yield in developing countries (hg/ha)	Leader countries	Sampled follower countries (Number)
Barley	49,603	15,345	Ireland, Netherlands, Zimbabwe, Switzerland, France	30
Cotton	30,703	11,867	Israel, Australia, Botswana, Guatemala, Syria	54
Maize	83,960	18,279	New Zealand, Israel, Jordan, Switzerland, Greece	77
Millet	15,552	8,031	Spain, Kenya, Hungary, China, Japan	38
Rice	64,970	27,154	Australia, Egypt, Spain, Japan, South Korea	70
Sorghum	44,820	12,852	Italy, France, Egypt, Israel, Spain	53
Soybean	22,936	12,286	Italy, Canada, Turkey, United States, Paraguay	28
Wheat	61,455	16,755	Netherlands, Ireland, United Kingdom, Denmark, France	42

Source: FAOSTAT (2013).

Note: hg = hectogram; ha = hectare.

As shown in Table 4.1, the total number of developing countries used in the subsequent crop-specific estimations ranges from 28 with soybean to 77 with maize. Table 4.1 also shows the average yield for each crop in the leader-country composite and across all developing countries included in the sample. For most crops, the developing-country average yields are less than half of the leader-country composite yield. When viewed over the time period in question, these yield differences are considerable, as shown in Figure 4.1.

Table 4.2 provides descriptive statistics for the remaining variables. Population size, our proxy for agricultural market size, is taken from World Bank (2012) for the time period 1961–2010. Harvested area is taken from FAO (2013) for the same time period. IPR regime strength is drawn from two separate sources. The primary source is the Ginarte–Park Index (Ginarte and Park 1997; Park and Wagh 2002; Park 2008; Park,³ personal communication, June 2012). This index covers the period 1960 to 2005 in five-year increments and scores countries' IPR regimes on a scale ranging from 0 to 5, with 5 being the strongest regime. The index is used widely in the IPR literature (Kanwar and Evenson 2003; Madsen and Timol 2011; Hudson and Minea 2013) and is preferred over other measures such as the Rapp–Rozeck Index (Rapp and Rozeck 1990) because of its thoroughness.

Table 4.2 Data summary

Variable	Variable explanation	Mean	Standard deviation	Minimum	Maximum
Gap_lag	Lagged value of yield gap	0.024	0.232	−1.441	1.254
ΔMKT (ΔPop)	Change in agricultural market size (population size)	0.114	0.042	−0.061	0.310
Δarea	Change in harvested area	0.045	0.480	−2.789	6.081
Comm	Dummy for highly commercialized or hybrid crops	0.334	0.472	0	1
ΔIPR_all	Change of IPR regime strength	0.227	0.447	−0.340	2.740
ΔIPR_plant	Changing in IPR coverage for plant varieties	0.024	0.152	0	1
ΔUPOV	Change in UPOV membership status	0.032	0.175	0	1

Source: FAOSTAT (2013), Ginarte and Park (1997), Park and Wagh (2002), Park (2008, 2012).

³ Walter G. Park, Professor, Department of Economics, American University, 4400 Massachusetts Avenue NW Washington, DC 20016-8029, USA (www.american.edu/cas/faculty/wgp.cfm).

The Ginarte–Park Index includes 18 measures of regime strength. Eleven of these measures are directly or indirectly relevant to the topic of appropriability and agricultural technology: coverage for plant and animal varieties and for microorganisms; membership in the International Union for the Protection of New Varieties of Plants (UPOV); measures for recourse against imitators; and protection, enforcement, and duration. Taken as a whole, the IPR regime strength score represents a signal to innovators about the potential for appropriating rents from their innovations transferred to and sold in a given developing country. However, since the aggregate index also covers IPR issues relevant to the manufacturing and service sectors, it is desirable to use a more refined IPR measure directly related to agriculture. To this end, we also introduce subindexes from the Ginarte–Park Index directly related to agriculture: coverage for plant and animal varieties, and membership in UPOV. We also introduce a narrower measure of IPR regime strength with a simple dummy for the years in which country i was a member of UPOV from UPOV (2012).

5. RESULTS

Using the data described above, we estimate the model specified in Equation (1) with an Arellano–Bond linear dynamic panel-data estimation approach. We estimate the model with two sets of specifications. First, we estimate crop-specific models to compare yield gap convergence across crops. Second, we estimate the model by pooling all crops to capture the overall effects of IPRs and other factors on yield gap convergence. Overall, our estimation results support the initial hypothesis that private-sector incentives affect the flow of yield-enhancing agricultural technologies from industrialized to developing countries (Tables 5.1 and 5.2). However, several particular results are worth noting.

Crop-Specific Estimations

Table 5.1a–c shows the crop-specific estimation results with different definitions of IPR regime strength, and it reports results from diagnostic tests required to validate the model. We observe several results that tentatively support the intuition underlying our model. First, our crop-specific estimations results indicate that all crops show decreasing yield gaps, that is, yield growth rate convergence over the past 50 years. The estimated diffusion parameters, β , are all less than 1 in absolute terms, although they vary in sign and significance levels. This suggests a decreasing yield gap across most crops. For example, the results for rice provide an estimate of β that is positive, less than 1, and significant under all definitions of IPR regime strength, which is consistent with the left-hand side of Figure 3.1. Results for barley, sorghum, and wheat—where the estimate of β is negative, less than 1, and significant under several specifications—may suggest that countries furthest from the frontier are experiencing yield growth rates that exceed those of the leader country but only for short periods of time, as in the right-hand side of Figure 3.1. Because these latter results suggest that our yield gap measures do not fully address short-term volatility in yields, we use the results as motivation for the pooled estimations discussed further below.

Second, and at odds with Goeschl and Swanson (2000), our crop-specific estimates do not suggest that hybrid crops—namely, maize and sorghum, as chosen in their study—exhibit significantly slower diffusion rates than other crops that may be attributable to the biological IPRs conferred by hybridization. Specifically, our estimates indicate that the coefficient for maize—the most extensively hybridized crop in the world—is less than 1, small in comparison to almost all other β values, and insignificant different from 0, suggesting rapid yield gap convergence.

Table 5.1a Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index measures

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.150 (0.097)	0.005 (0.059)	0.019 (0.061)	−0.094 (0.109)	0.137*** (0.050)	−0.128* (0.076)	0.092 (0.118)	−0.126* (0.073)
γ_1	ΔMKT_{it}	0.111 (0.139)	0.118 (0.125)	0.685*** (0.199)	−0.156 (0.160)	−0.051 (0.091)	0.370** (0.146)	0.062 (0.206)	0.131 (0.115)
γ_2	$\Delta Area_{it}$	0.065 (0.047)	0.023 (0.031)	−0.007 (0.053)	−0.006 (0.036)	0.021 (0.035)	0.061 (0.043)	−0.050 (0.062)	−0.035 (0.039)
θ_1	ΔIPR_{it}	0.032* (0.019)	−0.000 (0.030)	−0.028 (0.028)	−0.085* (0.045)	−0.015 (0.018)	−0.004 (0.037)	−0.003 (0.036)	−0.016 (0.013)
θ_2	$\Delta IPR_{i,t-1}$	−0.054* (0.032)	0.001 (0.024)	−0.022 (0.026)	0.002 (0.059)	−0.039*** (0.012)	−0.060 (0.058)	−0.026 (0.028)	−0.033 (0.022)
θ_3	$\Delta IPR_{i,t-2}$	0.016 (0.026)	0.083** (0.041)	−0.045 (0.038)	−0.067* (0.034)	−0.028* (0.015)	−0.021 (0.041)	0.015 (0.039)	−0.029 (0.025)
AR(1) z stat (Pr>z)		−2.4 (0.02)	−3.6 (0.00)	−4.0 (0.00)	−2.4 (0.02)	−3.7 (0.00)	−2.5 (0.02)	−2.5 (0.01)	−2.9 (0.00)
AR(2) z stat (Pr>z)		1.1 (0.29)	0.1 (0.96)	−1.7 (0.08)	−2.6 (0.01)	−0.6 (0.54)	0.4 (0.71)	0.3 (0.75)	0.2 (0.87)
Hansen J st (Pr> χ^2)		13.7 (0.55)	25.5 (0.33)	4.01 (0.02)	28.1 (0.21)	23.9 (0.41)	16.1 (0.58)	14.5 (0.91)	19.0 (0.7)
Diff-in-Hansen J stat (Pr> χ^2)		6.3 (0.50)	6.7 (0.46)	3.3 (0.86)	6.5 (0.48)	7.9 (0.34)	5.0 (0.67)	−1.1 (1.00)	3.8 (0.80)
Number of countries		30	54	77	38	70	53	28	42
Number of instruments		31	36	36	36	36	36	31	36
Number of observations		210	378	539	266	490	371	196	294

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the *10%, **5%, and ***1% levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations.

Table 5.1b Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index subcategory measures

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.135 (0.116)	0.005 (0.060)	0.043 (0.060)	−0.090 (0.106)	0.138*** (0.054)	−0.111 (0.072)	0.066 (0.108)	−0.116 (0.081)
γ_1	ΔMKT_{it}	0.055 (0.134)	0.181 (0.118)	0.529*** (0.178)	−0.373*** (0.128)	−0.150* (0.082)	0.261** (0.109)	0.083 (0.190)	0.034 (0.099)
γ_2	$\Delta Area_{it}$	0.094* (0.052)	0.028 (0.033)	−0.012 (0.054)	0.007 (0.038)	0.024 (0.035)	0.066* (0.039)	−0.061 (0.058)	−0.016 (0.039)
θ_1	$\Delta IPR_{-} Plant_{i,t}$	0.076 (0.067)	0.070 (0.062)	−0.041 (0.067)	0.020 (0.058)	−0.033 (0.034)	0.105 (0.105)	−0.069 (0.116)	0.017 (0.048)
θ_2	$\Delta IPR_{-} Plant_{i,t-1}$	−0.082 (0.052)	0.048 (0.056)	0.013 (0.080)	−0.044 (0.116)	−0.028 (0.028)	−0.100* (0.055)	0.046 (0.074)	−0.083*** (0.029)
θ_3	$\Delta IPR_{-} Plant_{i,t-2}$	−0.004 (0.082)	0.004 (0.041)	0.135 (0.088)	−0.060 (0.085)	−0.043 (0.057)	−0.040 (0.044)	0.058 (0.049)	−0.000 (0.129)
AR(1) z stat (Pr>z)		−3.7 (0.00)	−3.6 (0.00)	−4.1 (0.00)	−2.4 (−0.02)	−3.7 (0.00)	−4.0 (0.00)	−2.5 (0.01)	−2.9 (0.00)
AR(2) z stat (Pr>z)		0.8 (0.40)	−0.0 (0.99)	−1.6 (0.11)	−2.7 (0.01)	−0.57 (0.57)	1.2 (0.25)	0.4 (0.71)	0.2 (0.87)
Hansen J stat (Pr> χ^2)		20.4 (0.31)	25.5 (0.32)	44.6 (0.00)	30.5 (0.14)	24.6 (0.37)	28.9 (0.18)	15.9 (0.60)	20.0 (0.64)
Diff-in-Hansen J stat (Pr> χ^2)		5.2 (0.63)	5.4 (0.61)	4.9 (0.67)	6.8 (0.46)	8.3 (0.31)	6.4 (0.49)	5.9 (0.55)	4.9 (0.67)
Number of countries		30	54	77	38	70	53	28	42
Number of instruments		31	36	36	36	36	36	31	36
Number of observations		210	378	539	266	490	371	196	294

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the *10%, **5%, and ***1% levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations.

Table 5.1c Arellano–Bond linear dynamic panel-data estimation with UPOV membership

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.193** (0.083)	0.001 (0.060)	0.032 (0.062)	−0.090 (0.104)	0.141*** (0.054)	−0.130* (0.076)	0.083 (−0.109)	−0.131* (0.075)
γ_1	ΔMKT_{it}	0.095 (0.144)	0.150 (0.125)	0.554*** (0.181)	−0.373*** (0.128)	−0.154* (0.082)	0.292*** (0.107)	−0.001 (−0.18)	0.062 (0.114)
γ_2	$\Delta Area_{it}$	0.086* (0.052)	0.026 (0.033)	−0.015 (0.054)	0.005 (0.037)	0.023 (0.036)	0.057 (0.038)	−0.043 (−0.044)	−0.027 (0.045)
θ_1	$\Delta UPOV_{i,t}$	0.002 (0.036)	0.047 (0.058)	−0.028 (0.048)	−0.036 (0.090)	−0.044 (0.028)	−0.025 (0.045)	0.007 (−0.042)	0.008 (0.029)
θ_2	$\Delta UPOV_{i,t-1}$	−0.054 (0.065)	0.069 (0.070)	0.004 (0.068)	0.018 (0.154)	0.020 (0.029)	−0.119* (0.062)	−0.047 (−0.071)	−0.051** (0.025)
θ_3	$\Delta UPOV_{i,t-2}$	0.008 (0.093)	0.127 (0.085)	−0.036 (0.089)	0.135*** (0.028)	−0.099** (0.042)	−0.116* (0.060)	0.120*** (−0.038)	−0.097*** (0.031)
AR(1) z stat (Pr>z)		−2.5 (0.01)	−3.7 (0.00)	−4.1 (0.00)	−2.5 (0.01)	−3.7 (0.00)	−3.8 (0.00)	−2.6 (0.01)	−2.9 (0.00)
AR(2) z stat (Pr>z)		1.0 (0.34)	0.1 (0.94)	−1.6 (0.11)	−2.8 (0.01)	−0.6 (0.55)	1.1 (0.27)	0.2 (0.84)	0.1 (0.93)
Hansen J stat (Pr> χ^2)		14.4 (0.70)	25.6 (0.32)	43.4 (0.01)	30.4 (0.14)	24.8 (0.36)	27.9 (0.22)	15.8 (0.61)	20.6 (0.61)
Diff-in-Hansen J stat (Pr> χ^2)		7.2 (0.41)	5.8 (0.56)	4.3 (0.74)	6.5 (0.48)	8.5 (0.29)	5.5 (0.61)	6.5 (0.49)	4.7 (0.70)
Number of countries		30	54	77	38	70	53	28	42
Number of instruments		30	35	35	35	35	35	30	35
Number of observations		210	378	539	266	490	371	196	294

Source: Authors' own estimation.

Note: UPOV = International Union for the Protection of New Varieties of Plants. Robust standard errors given in parentheses. Coefficient estimates are significant at the *10%, **5%, and ***1% levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations.

Third, we observe a relationship between legal IPRs and yield gap convergence captured by the coefficient θ . Table 5.1a shows the estimation results using the aggregate Ginarte–Park Index, indicating that an increase in IPR regime strength is associated with yield gap convergence for most of the crops. As expected, the effect is most significant for 5- and 10-year lags, although sign and significance vary when moving from the Ginarte–Park Index (Table 5.1a) to the plant variety protection subcomponent of the index (Table 5.1b) to UPOV membership (Table 5.1c). In general, legal IPRs seem to be associated with yield gap convergence for rice, sorghum, and wheat, although interpretation of coefficient values for the Ginarte–Park Index is made difficult by the ordinal measurement, such that increases in index values are not necessarily comparable.

Fourth, we observe that our controls for growth in market size and cultivated area are ambiguous or insignificant. Coefficient estimates are positive and significant for maize and sorghum with the overall IPR index (Table 5.1a), but negative and significant for some other crops like millet and rice when specific IPR indexes are used (Tables 5.1b and 5.1c). Similarly, the estimated effect of harvested area is insignificant, suggesting that extensification and area expansion into more marginal land has little effect on yield gap convergence. Arguably, these results suggest that our data do not support the hypothesis that growth in market and growth in cultivated area have a strong effect on yield gap convergence.

Pooled Estimations and Robustness Checks

Since our unit of measurement of these estimations—change in the yield growth rate—is comparable across all crops and our key explanatory variables are not crop specific, we can pool the data together and estimate a set of similar models to generate additional results and test the robustness of our original specification. Results from the pooled estimation show coefficient estimates similar to the crop-specific estimations, indicating significant yield gap convergence and negative and significant effects from legal IPRs, primarily in the five-year lags (Table 5.2, Model 1).

Table 5.2 Arellano–Bond linear dynamic panel-data estimation with pooled data

Coefficient	Variable	Model 1	Model 2: with interaction	Model 3: plant variety protection	Model 4: UPOV
β_1	$G_{i,t-1}$	−0.018 (0.030)	0.134** (0.058)	0.139** (0.058)	0.137** (0.058)
β_2	$\text{Comm} * G_{i,t-1}$		−0.401*** (0.068)	−0.404*** (0.069)	−0.403*** (0.069)
γ_1	ΔMKT_{it}	0.097 (0.128)	0.074 (0.140)	0.185 (0.136)	0.153 (0.137)
γ_2	$\Delta Area_{it}$	0.000 (0.017)	−0.008 (0.017)	−0.007 (0.017)	−0.007 (0.017)
θ_1	ΔIPR_{it}	−0.014 (0.011)	−0.014 (0.011)		
θ_2	$\Delta IPR_{i,t-1}$	−0.034*** (0.011)	−0.039*** (0.011)		
θ_3	$\Delta IPR_{i,t-2}$	−0.007 (0.013)	−0.008 (0.013)		
	$\Delta IPR_Plant_{i,t}$			0.023 (0.023)	
	$\Delta IPR_Plant_{i,t-1}$			−0.037* (0.020)	

Table 5.2 Continued

Coefficient	Variable	Model 1	Model 2: with interaction	Model 3: plant variety protection	Model 4: UPOV
	$\Delta IPR_Plant_{i,t-2}$			0.040 (0.029)	
	$\Delta UPOV_{i,t}$				-0.013 (0.020)
	$\Delta UPOV_{i,t-1}$				-0.030 (0.022)
	$\Delta UPOV_{i,t-2}$				0.003 (0.029)
AR(1) z statistics (Pr>z)		-10.0 (0.000)	-9.5 (0.000)	-9.4 (0.000)	-9.4 (0.000)
AR(2) z statistics (Pr>z)		-1.0 (0.337)	-0.5 (0.652)	-0.4 (0.719)	-0.4 (0.697)
Hansen J statistics (Pr> χ^2)		56.7 (0.006)	58.4 (0.004)	57.4 (0.005)	58.2 (0.004)
Difference-in-Hansen J statistics (Pr> χ^2)		12.9 (0.07)	6.0 (0.539)	5.8 (0.569)	6.0 (0.544)
Number of groups		392	392	392	392
Number of instruments		54	55	55	55
Number of observations		2,744	2,744	2,744	2,744

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the *10%, **5%, and ***1% levels, respectively. Coefficients for fixed-year effects and crop dummies are omitted because of space limitations. UPOV = International Union for the Protection of New Varieties of Plants.

The pooled estimation model allows us to explore several other hypotheses. First, to specifically test if crop reproductive biology (that is, hybridization) affects yield gap convergence, we create a dummy variable that is interacted with the lagged yield gap variable to capture whether yield-enhancing technologies are embodied in hybrids versus open or self-pollinating varieties. Here, we choose maize and cotton but omit sorghum. We choose maize because of the well-documented yield-enhancing effects of commercial hybrid seed sold in both developed and developing countries cited earlier. We choose cotton because cotton seed—whether hybrid or not—is typically purchased by farmers from commercial suppliers rather than saved due to the difficulties in extracting seed from cotton lint for subsequent planting. We omit sorghum because of the overwhelming absence of hybrid sorghum in African countries south of the Sahara. We also omit soybean, which, though highly commercialized in Latin America through the introduction of herbicide-tolerant genetically modified varieties, has been a factor for consideration only since 2000 at the earliest (Trigo et al. 2010).

With the introduction of this interaction dummy, the estimation model becomes

$$G_{it} = c_i + \beta_1 G_{i,t-1} + \beta_2 (Comm * G_{i,t-1}) + \gamma_1 \Delta MKT_{it} + \gamma_2 \Delta Area_{it} + \sum_{j=1}^2 \theta_j E(\varepsilon_{it} \Delta IPR_{i,t-j-1}) + \varepsilon_{it} \quad (4)$$

where *Comm* denotes the two crops that are more highly commercialized in terms of their reproductive biology. Estimates of β_2 and θ_2 are both negative and significant (Table 5.2, Model 2), suggesting more rapid yield gap convergence for commercialized crops like maize and cotton relative to other crops, particularly under the (lagged) effects of a stronger IPR regime. Alternative definitions of this interaction dummy—including just maize and sorghum, as in the original Goeschl and Swanson (2000) model, or cotton, maize, and sorghum—yield similar results (Appendix C). This implies that commercialization (in our narrow definition) may, in general, incentivize technology transfers that result in yield gap convergence between developed and developing countries.

Next, we explore whether alternative measures of IPR regime strength affect yield gap convergence. As with the crop-specific estimations, we introduce the measure of patentability of plant varieties from the Ginarte–Park Index and membership status in UPOV. Estimated coefficients suggest that the patentability of plant varieties has a similar significant effect on yield gap convergence, but joining UPOV does not (Table 5.2, Model 3 and Model 4, respectively).

Next, we explore the choice of countries used in our estimations and the definition of leader country. First, we return to the crop-specific estimations to address the issue of whether variation in the countries used in each model might affect our results. We re-estimate our model using an identical set of 38 countries for cotton, maize, rice, and sorghum, noting that the remaining crops are not cultivated by a sufficient set of countries to replicate this test further. Results (Appendix D, Table D.1) are generally consistent with our initial estimation results, suggesting that results are not driven by variation in countries chosen for each crop-specific estimation. Second, we re-estimate the crop-specific Model 1 and our pooled Model 2 with three alternative measures of leader country. These alternative measures are (1) fixing the leader as the top country with the highest average yields across the entire period, (2) fixing the top three countries in the same manner, and (3) choosing the country with the highest yield in each year as the leader. Results (Appendix E) suggest that alternative compositions are inconsequential to our estimation results.

Next, we control for the possibility that crop, water, and soil management practices and other production techniques beyond cultivar improvement are, in fact, not time invariant across countries as given in our model. This is a possible explanation of yield gap convergence but one that is also difficult to isolate because management practices are crop specific, highly diverse, and poorly recorded in national time-series data. In an effort to address this issue, we include three variables to capture changes in agricultural mechanization (tractors per 100 square kilometers of arable land), irrigated agricultural land (percentage of total agricultural land under irrigation), and fertilizer consumption (kilograms per hectare of arable land) in the pooled estimation, using data from World Bank (2012). Coefficient estimates for these variables are mostly insignificant, and our main findings remain relatively unchanged (Appendix F).

Discussion

Overall, results from our estimations are consistent with respect to yield gap convergence, consistent across varying definitions of legal and biological IPRs, and robust across models that use both crop-specific and pooled data. Alternative compositions of leader countries and controls for crop management practices yield similarly consistent results. Although these results are subject to several alternative interpretations that we explore shortly, our findings support the argument that yield gap convergence between developed and developing countries during the period 1961–2010 is partly attributable to broad combinations of technological, institutional, and structural factors relating to both biological and legal IPRs. While legal IPRs play a role in yield gap convergence for some crops, the extent of the crop’s commercialization—the necessity of purchasing commercial seed rather than saving seed from harvest—seems to be a strong driver. These findings further suggest that the combination of legal and biological IPRs may provide a strong set of innovation incentives for technology transfer in agriculture, as shown with maize and cotton relative to the other crops examined above. This runs counter to arguments that temporary monopolies afforded by IPRs tend to limit technology transfers to developing countries, but it is not applicable to all crops investigated here.

Necessarily, there are alternative explanations and interpretations. First, it is clear that determinants of yield gap convergence are highly crop specific, meaning that general conclusions about biological and legal IPRs cannot be drawn to the satisfaction of either opponents or proponents of stronger IPR regimes, whether through legal or technological means. Second, it is possible to interpret the contribution of IPR regime strength to yield gap convergence as a proxy for generalized improvement in the policy and investment climate for innovative firms rather than a specific incentive to plant breeders, seed companies, or other agriculture-sector players.

Third—and despite the extensive evidence suggesting that cultivar improvement has been a major contributor to yield gap convergence and productivity growth in developing-country agriculture—we recognize that yield growth is always an interaction between genetics and environment, such that the absence of sufficiently high-resolution data on crop, soil, and water management limits any investigation of yield gap convergence. Although we attempt to address this with several alternative specifications of the model, it is unlikely that nationally aggregated data will be satisfying in this regard. Finally, a more complete treatment of the economic relationship between agricultural productivity growth and IPRs requires the inclusion of economic variables such as total factor productivity growth rather than yield growth as its dependent variable, as well as more appropriate, crop-specific time-series data on innovation incentives, including private-sector technology transfers and R&D spending.

Nonetheless, our findings should motivate continued discussion on the appropriate role of IPRs in developing-country agriculture, especially given the renewed global interest in agricultural productivity growth that followed the 2007–2008 global food price crisis. If the past 50 years are any indication, future growth in developing-country crop yields will rely significantly on innovation incentives directed toward accelerating the rate of cultivar improvement. Future investment in cultivar improvement may increasingly emerge from the private sector, given the commercial viability of new technologies (including biotechnology and genetic modification) and rising purchasing power among farmers and consumers in many developing countries. As such, future productivity growth will depend on the ability of developing-country policymakers to provide private innovators with the “right” incentives to encourage productivity-enhancing investments in R&D.

6. CONCLUSION

Through a refinement of Goeschl and Swanson (2000), this paper examines the extent to which biological and legal IPRs encourage or constrain technology transfers from developed to developing countries. It does so with a model that decomposes yield gap convergence into four distinct components—technological, production, institutional, and structural—that affect the flow of yield-enhancing technologies from developed to developing countries. The model is estimated using data from the period 1961–2010 and an Arellano–Bond linear dynamic panel-data estimation approach.

Because the model focuses only on yield gaps, there are limits to what can be extracted with regard to wider issues of agricultural productivity growth in developing countries. Nonetheless, findings indicate that both biological and legal forms of IPRs promote yield gap convergence, with effects varying significantly between crops. Technological mechanisms, namely biological IPRs, seem to contribute to yield gap convergence that derive from crop reproductive biology for crops such as maize and cotton. Importantly, these findings refute those of Goeschl and Swanson (2000), who found that hybrid crops exhibit significantly slower yield gap convergence rates than other crops.

Legal IPRs, on the other hand, seem to contribute most significantly through the lagged effects of a broad strengthening of IPR regimes, rather than through IPRs that are specific to agriculture. This may suggest that changes in IPR regime strength are proxies for broader economic policy reforms such as trade liberalization, public investment in science and innovation, or other indirect mechanisms. Alternative explanations or interpretations may also exist.

Our results further suggest that combinations of biological and legal IPRs may incentivize technology transfers to developing countries and that yield gap convergence attributable to these incentives may result from greater innovative activity in the private sector. However, the crop specificity of our findings also suggests that policies designed to strengthen IPRs as they relate to agriculture may also be insufficient in stimulating broad-based private innovation and yield gap convergence. In sum, our conclusions about biological and legal IPRs are unlikely to satisfy either opponents or proponents of stronger IPR regimes, whether in academia, policymaking, or private enterprise. However, they do point to the potential importance of crop-specific analysis, policies, and investments.

APPENDIX A: DERIVATION OF THE EMPIRICAL MODEL

Following Goeschl and Swanson (2000) and other economic growth literature, an empirical model to test the convergence of growth rates between the leader and follower countries takes the following form:

$$G_{it} = \alpha_i + \beta G_{i,t-1} + \varepsilon, \quad (\text{A.1})$$

where G_{it} is the gap in growth rates between the country i and the leader country. The yield gap in growth rates can be further defined as

$$G_{it} = \frac{Y_t^* - Y_{t-1}^*}{Y_{t-1}^*} - \frac{Y_{it} - Y_{i,t-1}}{Y_{i,t-1}} = \frac{Y_t^*}{Y_{t-1}^*} - \frac{Y_{it}}{Y_{i,t-1}},$$

where Y_{it} is the yield of country i in time t and Y_t^* is the yield in the leader country. We assume a higher growth rate in the leader country and define the gap as a positive number.

Empirically, we use the logarithmic form of the yield with $y_{it} \equiv \log(Y_{it})$ and $y_t^* \equiv \log(Y_t^*)$. Note that the logarithmic transformation is used here for ease of notation and to ensure comparability with the results generated by Goeschl and Swanson (2000).

Using this form of the yield, we denote the gap in growth rates as

$$G_{it} = \log\left(\frac{Y_t^*}{Y_{t-1}^*}\right) - \log\left(\frac{Y_{it}}{Y_{i,t-1}}\right) = y_t^* - y_{t-1}^* - (y_{it} - y_{i,t-1}) = \Delta y_t^* - \Delta y_{it}$$

Rearrange Equation (A.1):

$$\Delta y_t^* - \Delta y_{it} = \alpha_i + \beta G_{i,t-1} + \varepsilon. \quad (\text{A.2})$$

We then obtain

$$\Delta y_{it} = \Delta y_t^* - \alpha_i - \beta G_{i,t-1} - \varepsilon. \quad (\text{A.3})$$

This equation is more intuitive in its economic interpretation. However, we use Equation (A.2) for the empirical analysis set forth in this paper.

APPENDIX B: THE STRICT EXOGENEITY ASSUMPTION

The specification given in Equation (7) is expressed as follows:

$$G_{it} = c_i + \beta G_{i,t-1} + \gamma_1 \Delta MKT_{it} + \gamma_2 \Delta Area_{it} + \theta_1 \Delta IPR_{it} + \theta_2 \Delta IPR_{i,t-1} + \theta_3 \Delta IPR_{i,t-2} + \varepsilon_{it} \quad (B.1)$$

Let $X_{it} = \{G_{i,t-1}, \Delta MKT_{it}, \Delta Area_{it}, \Delta IPR_{it}, \Delta IPR_{i,t-1}, \Delta IPR_{i,t-2}\}$. We assume that the idiosyncratic error in the current time period is uncorrelated with all the explanatory variables in the past, that is,

$$E(\varepsilon_{it} \mid X_{i,1}, X_{i,2}, \dots, X_{i,t-1}, c_i) = 0$$

The strict exogeneity assumption for estimating the parameters in the model is

$$E(\varepsilon_{it} \mid X_{i,1}, X_{i,2}, \dots, X_{i,T}, c_i) = 0, \quad t = 1, 2, \dots, T. \quad (B.2)$$

That is, ε_{it} is uncorrelated with the explanatory variables in *each* time period. The strict exogeneity assumption is violated in our estimation model because of the lagged value of the yield gap ($G_{i,t-1}$). The reason is that the lagged value of the yield gap $G_{i,t-1}$ is a function of the lagged idiosyncratic error $\varepsilon_{i,t-1}$, so ε_{it} will be correlated with $(G_{i,t+1}, \dots, G_{i,T})$. For example,

$$\begin{aligned} E(\varepsilon_{it} G_{it}) &= E(\varepsilon_{it} c_i) + \beta E(\varepsilon_{it} G_{i,t-1}) + \gamma_1 E(\varepsilon_{it} \Delta MKT_{it}) + \gamma_2 E(\varepsilon_{it} \Delta Area_{it}) \\ &+ \sum_{j=1}^2 \theta_j E(\varepsilon_{it} \Delta IPR_{i,t-j-1}) + E(\varepsilon_{it}^2) = E(\varepsilon_{it}^2) > 0. \end{aligned} \quad (B.3)$$

APPENDIX C: POOLED ESTIMATION WITH CONTROLS FOR ALTERNATIVE SPECIFICATIONS OF HYBRIDIZED AND COMMERCIALIZED CROPS

Table C.1 Arellano–Bond linear dynamic panel-data estimation (pooled data)

Coefficient	Variable	Hybrid 1 (maize, sorghum)	Hybrid 2 (maize, sorghum, cotton)
β_1	$G_{i,t-1}$	0.180*** (0.049)	0.337*** (0.078)
β_2	Hybrid * $G_{i,t-1}$	−0.521*** (0.061)	−0.662*** (0.084)
γ_1	ΔMKT_{it}	0.093 (0.141)	0.066 (0.152)
γ_2	$\Delta Area_{it}$	0.005 (0.017)	−0.005 (0.017)
θ_1	ΔIPR_{it}	−0.024** (0.011)	−0.019* (0.011)
θ_2	$\Delta IPR_{i,t-1}$	−0.036*** (0.011)	−0.041*** (0.011)
θ_3	$\Delta IPR_{i,t-2}$	−0.005 (0.013)	−0.005 (0.013)
AR(1) z statistics (Pr>z)		−9.8 (0.000)	−9.1 (0.000)
AR(2) z statistics (Pr>z)		−0.9 (0.372)	−0.7 (0.485)
Hansen J statistics (Pr> χ^2)		52.8 (0.016)	54.3 (0.011)
Difference-in-Hansen J statistics (Pr> χ^2)		8.8 (0.265)	5.2 (0.636)
Number of groups		392	392
Number of instruments		55	55
Number of observations		2,744	2,744

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the *10%, **5%, and ***1% levels, respectively. Coefficients for fixed-year effects and crop dummies are omitted because of space limitations.

APPENDIX D: ESTIMATION RESULTS WITH ALTERNATIVE DATASETS

Table D.1 Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index measures (four crops grown by the same countries)

Coefficient	Variable	Cotton	Maize	Rice	Sorghum
β	$G_{i,t-1}$	−0.012 (0.042)	−0.011 (0.095)	0.137** (0.057)	−0.136* (0.082)
γ_1	ΔMKT_{it}	0.089 (0.157)	0.880*** (0.201)	−0.084 (0.138)	0.385** (0.154)
γ_2	$\Delta Area_{it}$	−0.005 (0.040)	−0.028 (0.143)	0.085 (0.065)	0.028 (0.039)
θ_1	ΔIPR_{it}	−0.024 (0.036)	−0.059** (0.027)	−0.001 (0.022)	−0.020 (0.037)
θ_2	$\Delta IPR_{i,t-1}$	0.007 (0.031)	−0.045 (0.041)	−0.038 (0.029)	−0.035 (0.060)
θ_3	$\Delta IPR_{i,t-2}$	0.078 (0.049)	−0.014 (0.038)	−0.037 (0.039)	−0.030 (0.038)
AR(1) z statistics (Pr>z)		−3.4 (0.00)	−3.0 (0.00)	−2.9 (0.00)	−3.1 (0.00)
AR(2) z statistics (Pr>z)		0.5 (0.64)	−0.8 (0.46)	−0.8 (0.44)	1.6 (0.11)
Hansen J statistics (Pr> χ^2)		22.8 (0.48)	31.6 (0.11)	28.5 (0.20)	23.5 (0.44)
Difference-in-Hansen J statistics (Pr> χ^2)		10.2 (0.18)	7.3 (0.40)	13.7 (0.06)	1.6 (0.98)
Number of countries		38	38	38	38
Number of instruments		36	36	36	36
Number of observations		266	266	266	266

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the * 10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations.

APPENDIX E: ESTIMATION RESULTS WITH DIFFERENT LEADER COUNTRY DEFINITIONS

Figure E.1 Yield frontier with different definitions (1,000 hg/ha)

Source: FAOSTAT (2013).

Note: The upper dashed line is a plot of the maximum yield each year, which may change from one leader country to another over time. The solid line right below it is the yield of the country that shows up the most in the top three countries over years (Top 1). The dashed line, which is almost overlapped with the dark solid line at the bottom, is the average yield of the top three countries that show up the most as in the top three country groups over years (Top 3). The dark solid line at the bottom is the yield frontier used in the current analysis (Top 5), which is the most stable among these four measures.

Table E.1 Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index measures using top five countries to define *leader country*

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.150 (0.097)	0.005 (0.059)	0.019 (0.061)	−0.094 (0.109)	0.137*** (0.050)	−0.128* (0.076)	0.092 (0.118)	−0.126* (0.073)
γ_1	ΔMKT_{it}	0.111 (0.139)	0.118 (0.125)	0.685*** (0.199)	−0.156 (0.160)	−0.051 (0.091)	0.370** (0.146)	0.062 (0.206)	0.131 (0.115)
γ_2	$\Delta Area_{it}$	0.065 (0.047)	0.023 (0.031)	−0.007 (0.053)	−0.006 (0.036)	0.021 (0.035)	0.061 (0.043)	−0.050 (0.062)	−0.035 (0.039)
θ_1	ΔIPR_{it}	0.032* (0.019)	−0.000 (0.030)	−0.028 (0.028)	−0.085* (0.045)	−0.015 (0.018)	−0.004 (0.037)	−0.003 (0.036)	−0.016 (0.013)
θ_2	$\Delta IPR_{i,t-1}$	−0.054* (0.032)	0.001 (0.024)	−0.022 (0.026)	0.002 (0.059)	−0.039*** (0.012)	−0.060 (0.058)	−0.026 (0.028)	−0.033 (0.022)
θ_3	$\Delta IPR_{i,t-2}$	0.016 (0.026)	0.083** (0.041)	−0.045 (0.038)	−0.067* (0.034)	−0.028* (0.015)	−0.021 (0.041)	0.015 (0.039)	−0.029 (0.025)

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the *10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations. The AR(2), Hansen, and difference-in-Hansen tests are passed for most cases.

Table E.2 Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index measures using top three countries to define *leader country*

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.162 (0.118)	−0.012 (0.049)	−0.008 (0.051)	−0.105 (0.114)	0.197*** (0.049)	−0.182** (0.080)	0.025 (0.103)	−0.175** (0.072)
γ_1	ΔMKT_{it}	0.002 (0.147)	0.147 (0.139)	0.723*** (0.177)	−0.396** (0.181)	0.064 (0.078)	0.409*** (0.155)	−0.168 (0.323)	0.270** (0.113)
γ_2	$\Delta Area_{it}$	0.093 (0.062)	0.051* (0.029)	0.015 (0.060)	−0.004 (0.045)	0.021 (0.031)	0.045 (0.051)	−0.065 (0.055)	−0.046 (0.050)
θ_1	ΔIPR_{it}	0.020 (0.023)	0.011 (0.044)	−0.029 (0.036)	−0.074 (0.055)	−0.017 (0.019)	−0.041 (0.028)	0.002 (0.040)	−0.022 (0.015)
θ_2	$\Delta IPR_{i,t-1}$	−0.033 (0.026)	0.010 (0.026)	0.006 (0.033)	0.011 (0.052)	−0.038** (0.016)	−0.022 (0.057)	−0.016 (0.027)	−0.024 (0.019)
θ_3	$\Delta IPR_{i,t-2}$	−0.003 (0.018)	0.084** (0.042)	−0.036 (0.033)	−0.053 (0.035)	−0.047*** (0.014)	−0.088*** (0.031)	0.038 (0.037)	−0.020 (0.029)

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the *10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations. The AR(2), Hansen, and difference-in-Hansen tests are passed for most cases.

Table E.3 Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index measures using the top country to define *leader country*

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.147 (0.150)	−0.036 (0.055)	−0.172*** (0.052)	−0.113 (0.083)	0.201*** (0.051)	−0.158** (0.066)	0.037 (0.105)	−0.119 (0.079)
γ_1	ΔMKT_{it}	−0.061 (0.178)	0.219 (0.152)	−0.236 (0.149)	0.327* (0.189)	−0.047 (0.118)	0.648*** (0.138)	0.138 (0.201)	0.196** (0.100)
γ_2	$\Delta Area_{it}$	0.087** (0.038)	0.037 (0.031)	0.016 (0.047)	−0.040 (0.045)	0.031 (0.050)	0.026 (0.057)	−0.082* (0.042)	−0.021 (0.046)
θ_1	ΔIPR_{it}	0.040* (0.023)	−0.074* (0.042)	−0.001 (0.024)	−0.198*** (0.062)	−0.031 (0.025)	−0.042 (0.033)	−0.013 (0.041)	−0.021 (0.018)
θ_2	$\Delta IPR_{i,t-1}$	−0.026 (0.036)	−0.088*** (0.032)	−0.048** (0.022)	−0.053 (0.068)	−0.069*** (0.020)	−0.051 (0.056)	−0.083** (0.032)	−0.031 (0.026)
θ_3	$\Delta IPR_{i,t-2}$	0.008 (0.023)	0.050 (0.035)	−0.014 (0.030)	−0.057 (0.048)	−0.063*** (0.023)	−0.036 (0.041)	0.009 (0.030)	−0.016 (0.029)

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the * 10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed-year effects are omitted because of space limitations. The AR(2), Hansen, and difference-in-Hansen tests are passed for most cases.

Table E.4 Arellano–Bond linear dynamic panel-data estimation with Ginarte–Park Index measures using maximum yield in each year to define *leader country*

Coefficient	Variable	Barley	Cotton	Maize	Millet	Rice	Sorghum	Soybean	Wheat
β	$G_{i,t-1}$	−0.143 (0.128)	−0.160*** (0.054)	0.063 (0.066)	−0.204* (0.122)	−0.179*** (0.064)	−0.243*** (0.087)	−0.014 (0.087)	−0.148** (0.073)
γ_1	ΔMKT_{it}	0.108 (0.145)	−0.109 (0.199)	0.443*** (0.142)	0.608*** (0.191)	−0.077 (0.114)	1.015*** (0.179)	−0.151 (0.221)	0.218** (0.100)
γ_2	$\Delta Area_{it}$	0.081* (0.044)	0.031 (0.045)	0.029 (0.053)	−0.065 (0.040)	−0.063 (0.053)	−0.000 (0.052)	0.023 (0.033)	−0.030 (0.044)
θ_1	ΔIPR_{it}	0.029 (0.023)	−0.003 (0.054)	0.015 (0.029)	−0.081 (0.061)	−0.049** (0.024)	0.069* (0.040)	0.022 (0.045)	−0.015 (0.013)
θ_2	$\Delta IPR_{i,t-1}$	−0.026 (0.028)	−0.058 (0.039)	−0.090*** (0.030)	−0.037 (0.094)	−0.032* (0.019)	0.176*** (0.053)	0.011 (0.037)	−0.017 (0.022)
θ_3	$\Delta IPR_{i,t-2}$	0.010 (0.017)	0.138** (0.057)	−0.069* (0.037)	−0.113*** (0.039)	−0.009 (0.019)	0.035 (0.059)	0.058 (0.040)	−0.034 (0.029)

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the * 10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed year effects are omitted because of space limitations. The AR(2), Hansen, and difference-in-Hansen tests are passed for most cases.

Table E.5 Arellano–Bond linear dynamic panel-data estimation, pooled data, Model 2

Coefficient	Variable	Top 5 countries	Top 3 countries	Top 1 country	Maximum yield each year
β_1	$G_{i,t-1}$	0.134** (0.058)	0.089 (0.058)	0.115* (0.061)	−0.005 (0.061)
β_2	$\text{Comm} * G_{i,t-1}$	−0.401*** (0.068)	−0.337*** (0.066)	−0.483*** (0.070)	−0.263*** (0.069)
γ_1	ΔMKT_{it}	0.074 (0.140)	0.104 (0.160)	0.088 (0.161)	0.268 (0.170)
γ_2	$\Delta Area_{it}$	−0.008 (0.017)	−0.010 (0.018)	−0.012 (0.018)	−0.017 (0.018)
θ_1	ΔIPR_{it}	−0.014 (0.011)	−0.016 (0.012)	−0.023* (0.013)	−0.006 (0.015)
θ_2	$\Delta IPR_{i,t-1}$	−0.039*** (0.011)	−0.027** (0.013)	−0.063*** (0.013)	−0.021 (0.015)
θ_3	$\Delta IPR_{i,t-2}$	−0.008 (0.013)	−0.012 (0.014)	−0.008 (0.016)	−0.006 (0.016)

Source: Authors' own estimation.

Note: Robust standard errors given in parentheses. Coefficient estimates are significant at the * 10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed-year effects and crop dummies are omitted because of space limitations. The AR(2) and difference-in-Hansen tests are passed for most cases.

APPENDIX F: POOLED ESTIMATION WITH CONTROLS FOR CHANGES OF CROP MANAGEMENT

Table F.1 Arellano–Bond linear dynamic panel-data estimation with controls for changes in crop management practices, pooled data, Model 2

Coefficient	Variable	Model 1	Model 2: with interaction	Model 3: plant variety protection	Model 4: UPOV
β_1	$G_{i,t-1}$	−0.039 (0.032)	0.104 (0.065)	0.101 (0.065)	0.091 (0.065)
β_2	$\text{Comm} * G_{i,t-1}$		−0.395*** (0.087)	−0.392*** (0.088)	−0.381*** (0.088)
γ_1	ΔMKT_{it}	0.241 (0.159)	0.217 (0.166)	0.322** (0.164)	0.277* (0.167)
γ_2	$\Delta Area_{it}$	0.003 (0.021)	−0.008 (0.021)	−0.006 (0.022)	−0.008 (0.022)
γ_3	$\Delta Machinery_{it}$	−0.018 (0.018)	−0.024 (0.017)	−0.025 (0.017)	−0.025 (0.017)
γ_4	$\Delta Irrigation_{it}$	0.015 (0.021)	0.022 (0.022)	0.025 (0.021)	0.029 (0.023)
γ_5	$\Delta Fertilizer_{it}$	−0.005 (0.012)	−0.004 (0.011)	0.000 (0.011)	−0.002 (0.011)
θ_1	ΔIPR_{it}	−0.010 (0.014)	−0.010 (0.015)		
θ_2	$\Delta IPR_{i,t-1}$	−0.033* (0.018)	−0.033* (0.019)		
θ_3	$\Delta IPR_{i,t-2}$	−0.012 (0.019)	−0.012 (0.019)		
	$\Delta IPR_Plant_{i,t}$			0.048 (0.030)	
	$\Delta IPR_Plant_{i,t-1}$			−0.006 (0.031)	
	$\Delta IPR_Plant_{i,t-2}$			0.043 (0.035)	
	$\Delta UPOV_{i,t}$				−0.003 (0.029)
	$\Delta UPOV_{i,t-1}$				0.010 (0.035)
	$\Delta UPOV_{i,t-2}$				−0.018 (0.040)

Table F.1 Continued

Coefficient	Model 1	Model 2: with interaction	Model 3: plant variety protection	Model 4: UPOV
AR(1) z statistics (Pr>z)	-7.6 (0.000)	-7.0 (0.000)	-7.0 (0.000)	-7.0 (0.000)
AR(2) z statistics (Pr>z)	-1.9 (0.062)	-1.6 (0.119)	-1.5 (0.126)	-1.6 (0.102)
	51.2			
Hansen J statistics (Pr> χ^2)	(0.023)	51.5 (0.021)	52.0 (0.019)	53.4 (0.014)
Difference-in-Hansen J statistics(Pr> χ^2)	13.1 (0.07)	12.3 (0.092)	12.2 (0.095)	12.5 (0.085)
Number of groups	298	298	298	298
Number of instruments	54	58	58	58
Number of observations	1,633	1,633	1,633	1,633

Source: Authors' own estimation.

Notes: Data for machinery, irrigation, and fertilizer are taken from the World Development Indicators from the World Bank (2013). Robust standard errors given in parentheses. Coefficient estimates are significant at the * 10 percent, ** 5 percent, and *** 1 percent levels, respectively. Coefficients for fixed-year effects and crop dummies are omitted because of space limitations. The AR(2) and difference-in-Hansen tests are passed for most cases. UPOV = International Union for the Protection of New Varieties of Plants.

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