Inappropriate Technology: Evidence from Global Agriculture*

Jacob Moscona† and Karthik A. Sastry‡

February 13, 2025

Abstract

An influential explanation for global productivity differences is that frontier technologies are adapted to the high-income countries that develop them and "inappropriate" elsewhere. We study this hypothesis in agriculture using data on novel plant varieties, patents, output, and the global range of crop pests and pathogens. Innovation focuses on the environmental conditions of technology leaders, and ecological mismatch with these markets reduces technology transfer and production. Combined with a model, our estimates imply that inappropriate technology explains 15-20% of cross-country agricultural productivity differences and re-shapes the potential consequences of innovation policy, the rise of new technology leaders, and environmental change.

*We thank Daron Acemoglu, Marios Angeletos, David Atkin, Abhijit Banerjee, Chris Barrett, Laura Boudreau, Arnaud Costinot, Dave Donaldson, John Friedman, Michela Giorcelli, Michael Goodin, Gabriel Kreindler, Matt Lowe, Erzo Luttmer, Martí Mestieri, Paul Novosad, Nathan Nunn, Ben Olken, Jesse Perla, James Robinson, Frank Schilbach, and Chris Udry for helpful comments. We are very grateful to Christine Sherratt and Hope Jansen for their help acquiring the CABI Crop Protection Compendium and to Tomochika Motomura for his support with the UPOV data, and Aidan Toner-Rodgers for assistance with the patent applicant classification. We also thank seminar participants at MIT, Harvard, University of British Columbia, University of Southern California, UC San Diego, UC Berkeley, Penn State, the Stockholm School of Economics, the IIES at Stockholm University, NYU, the NEUDC, the RIDGE Virtual Forum, the NBER Development Economics/BREAD Fall Meeting, the NBER Macroeconomics and Productivity Summer Institute, the European Meeting of the Econometric Society, the WIDER Development Conference at Universidad de los Andes, Stanford, Stanford GSB, HBS, Princeton, Yale, Chicago Booth, Cornell, Tel Aviv University, Hebrew University, Hong Kong University, ShanghaiTech, Chinese University of Hong Kong-Shenzhen, Sciences Po, FGV Sao Paulo, PUC Rio, Northwestern Kellogg, University of Minnesota (Applied Economics), Rutgers AFRE, the American Society for Virology Annual Meeting, and Iowa State for helpful feedback. Zhuokai Huang, Rada Pavlova, and Miriam Zuo provided excellent research assistance.

†MIT, email: `moscona@mit.edu`; website: `https://economics.mit.edu/people/faculty/jacob-moscona`

‡Princeton University, email: `ksastry@princeton.edu`; website: `https://www.karthiksastry.com`

1. Introduction

Research and development (R&D) is concentrated in a small number of high-income countries (Boroush, 2020). To what extent does this phenomenon underlie global disparities in productivity?

One answer to this question presumes that the most transformative ideas are broadly applicable and easily transmittable. Therefore, technology diffusion erodes disparities in the long run regardless of the global distribution of R&D and barriers to technology adoption are the main drivers of global inequality (Parente and Prescott, 1994; Barro and Sala-i Martin, 1997). A second answer, however, emphasizes that new technologies are attached to specific conditions and characteristics of production (Atkinson and Stiglitz, 1969). According to this *inappropriate technology hypothesis*, R&D leaders develop technologies that are suitable for local conditions but unproductive in others (Stewart, 1978; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001). Low technology diffusion is a natural consequence, even without frictions to technology adoption. Disparities in global technology use and productivity are driven by the incentives faced by *innovators* rather than those faced by adopters.

The premises of the inappropriate technology hypothesis loom especially large in agriculture. This may be best illustrated via an example. The Corn Rootworm is nicknamed the "Billion-Dollar Bug" in the United States biotechnology industry for its impact on corn production (Nordhaus, 2017). Developing technology that confers resistance against this foe is the focus of a significant R&D effort, an important achievement of which is the development of genetically modified varieties that are toxic to Corn Rootworms but not other fauna (Bessin, 2019). These tools are precisely engineered to target a pest that is common in the US. But they are not intentionally designed to target the pests that decimate corn production elsewhere in the world, like the Maize Stalk Borer that is endemic to sub-Saharan Africa and estimated to cause corn losses in Kenya of 10-20% (De Groote, 2002).

Beyond a handful of case studies, however, little is known about the inappropriate technology hypothesis in global agriculture or any other sector. In particular, is agricultural innovation systematically directed toward the environmental conditions of technology leaders? If so, does the mismatch between frontier innovation and local ecological conditions in much of the world systematically reduce the global diffusion of agricultural technology? And to what extent does this force explain the immense cross-country disparities in agricultural productivity?

This paper investigates each pillar of the inappropriate technology hypothesis in the context of global agriculture. First, we show that agricultural innovation is strongly directed toward the specific ecological characteristics of high-income, R&D-intensive countries. Second, using a new measure of environmental mismatch that varies at the level of country pairs and crops, we show that mismatch significantly reduces the global diffusion of agricultural technology, especially from more to less innovative countries. Finally, we show that environmental mismatch with those innovative countries reduces agricultural output. We interpret these results via a model that endogenizes global agricultural productivity as the product of unevenly appropriate innovation, and we use the model to study counterfactual changes to global research and the environment. Together, these results provide strong evidence for the inappropriate technology hypothesis—linking its premises to its predictions—as well as a framework to measure its incidence in a critical sector.

Model. We first introduce a model of inappropriate technology in global agriculture. We build on a standard framework for agricultural technology use, crop choice, and demand (as in, e.g., Costinot et al., 2016) by adding an innovative sector in a "Leader" country. The innovator invests in R&D to improve technology along margins that are specific to certain environmental conditions. Because of differences in profit opportunities and costs, innovation is endogenously directed to the environmental conditions of the Leader. Thus, places that are more environmentally similar to the leader receive more technology transfer and have higher productivity. The model motivates our empirical strategy to measure environmental mismatch and its relationship with technology diffusion and output. The model also provides a structural interpretation of our estimating equations, which we later exploit to study counterfactuals.

Measurement. To study the inappropriate technology hypothesis, we need to measure: (i) the environmental conditions to which technologies are adapted, (ii) the between-location *mismatch* in these conditions, (iii) agricultural innovation and technology diffusion, and (iv) agricultural output.

We first introduce a novel method to measure environmental conditions and environmental mismatch in agriculture using systematic data on crop pests and pathogens (CPPs). CPPs—including viruses, bacteria, parasitic plants, insects, and fungi—are estimated to reduce global output by 50-80% (Oerke and Dehne, 2004), and CPP resistance is a key focus of both traditional plant breeding and modern transgenic crop development (Dong and Ronald, 2019). Using data from the Centre for Agriculture and Bioscience International's Crop Protection Compendium (CPC), which are based on expert review of published literature in plant pathology and agronomy (Pasiecznik et al., 2005) and widely used in ecological sciences (see, e.g., Savary et al., 2019), we record the global range and agricultural host plants for all known, economically relevant CPPs. This approach picks up precise variation in environmental conditions across both locations and crops.[1]

Combining the CPP data with techniques from population ecology (Jost et al., 2011), we construct a measure of "CPP mismatch" that summarizes the difference in the species composition of CPPs affecting a crop in different locations. This measure incorporates variation across country pairs, which have different local CPPs, and across crops, which are hosts to different CPPs. We use CPP mismatch as our main shifter of "potential inappropriateness" of agricultural technologies transferred from one environment to another.

We next develop several measures of agricultural innovation and technology diffusion. First, we build a novel data set on all international instances of intellectual property (IP) protection for plant varieties using a proprietary dataset from the International Union for the Protection of New Varieties of Plants (UPOV). UPOV's unique variety identifiers allow us to track individual varieties from their first introduction in one country to their subsequent transfer to others. Second, we compile all utility patents related to agricultural technology and, using the title and abstract, link them to specific crops and CPPs. We track cross-border transfers via both patent families and patent citations. Together, these measures allow us to quantify both the "downstream" introduction of improved inputs that

[1] To account for the importance of other environmental differences, we also develop independent measures of agro-climatic environmental differences (e.g., in temperature and soil characteristics).

embody productivity enhancements and the "upstream" flows of technical knowledge.

Finally, we compile global data at the crop-by-country level on crop-specific output from the Food and Agriculture Organization Statistics (FAOSTAT) database. We also collect data on crop-specific output for each state in Brazil and India using the latest agricultural census from both countries.

Empirical Findings. We first document that agricultural innovation is strongly directed toward the environmental conditions of R&D leaders. The raw data reveal how central CPPs are to agricultural technology: almost two-thirds of all patents mention at least one CPP by name. But not all CPPs get equal focus. For example, a CPP that is present in the US is, on average, mentioned in more than five times as many patents as one that is not. Using cross-sectional variation, we show that this finding is explained by a general focus on larger markets—but only if they enforce intellectual property (IP) protection for plant biotechnology—as well as a strong "home bias" toward locally present CPPs.

We next show that environmental mismatch substantially reduces the cross-border transfer of technology. Our estimating equation, derived from the model, sweeps out possible confounds at the origin-by-crop level (e.g., origin market size, technology, and income), destination-by-crop level (e.g., destination market size, technology, and income), or the country-pair level (e.g., distance) as fixed effects. Thus, our empirical strategy exploits fine-grained variation at the level of crops and country-pairs. Mismatch reduces the transfer of novel agricultural inputs (measured via plant variety transfer), the transfer of agricultural inventions (measured via patent families), and knowledge flows (measured via patent citations). Our estimates imply that CPP dissimilarities reduce the international diffusion of crop varieties by 30% for the median crop and country-pair. As a placebo test, we show that there is no comparable effect of mismatch on the diffusion of mechanical technologies (e.g., harvesters), whose productivity should be less affected by the local environment. To demonstrate that our finding is not relevant for only markets with IP protection, we also show that mismatch inhibits the introduction of new varieties in sub-Saharan Africa, as measured by the CGIAR's Diffusion and Impact of Improved Varieties in Africa (DIIVA) Project, and the diffusion of high-yield varieties from the Green Revolution, as measured by Evenson and Gollin (2003b).

A further prediction of our model is that the effect of mismatch scales with the intensity of innovation in technological *origin countries*, but need not be related to characteristics of *destination countries*. Three additional results are consistent with this prediction. First, mismatch with technological leaders, identified in our data as the countries (for each crop) that produce the most novel varieties, has a 30 times larger effect on technology transfer than mismatch with other countries. By contrast, in our preferred specification, mismatch with countries other than the leaders has no statistical effect on technology transfer. Second, the effect of ecological mismatch is substantially larger for crops that are more central to recent R&D efforts, like those with genetic modification technology. Finally, there is no economically or statistically meaningful heterogeneity of our estimates across a range of proxies for the development stage of destinations. Mismatch inhibits technology diffusion to countries rich or poor, abundant or scarce in human capital, and high or low in the use of other chemical inputs.

Having established that mismatch inhibits the diffusion of agricultural technology, we next empirically document that mismatch with R&D leaders reduces agricultural output. Our estimating equation, derived from the model, exploits within-country and within-crop variation. Our baseline estimate implies that a one-standard-deviation increase in CPP mismatch with the frontier reduces crop-specific production by 0.42 standard deviations. The effect size is similar after flexibly controlling for innate suitability—the key residual variation in the model—using both external agroclimatic models of potential yield (FAO GAEZ) as well as a machine-learning approach.

We pursue three complementary strategies to validate a causal interpretation of this result. First, in a falsification exercise, we re-estimate our regression replacing our main independent variable with CPP mismatch to each country in the world. The effect of CPP mismatch with *non-leader* countries is centered around zero and the effect of mismatch with leaders is in the far tail of the effect size distribution. Second, we find quantitatively similar effects of CPP mismatch on production within countries using state-level data from India and Brazil. By including country-by-crop fixed effects in this strategy, we fully absorb any characteristics that vary across crop-country pairs like trade and agricultural policy, local R&D, or country-specific features of input demand.

Finally, we exploit two shifts in the direction of global agricultural innovation as natural experiments. Exploiting *changes* in the direction of technology makes it possible to fully absorb static differences across crop-country pairs and control for trends in initial productivity. We first study the Green Revolution of the 1960s and 1970s, an effort to shift agricultural innovation toward certain tropical regions. We show that this change in the global focus of innovation led to a greater expansion of production in places with lower mismatch with centers of Green Revolution breeding. Second, we study the rise of US biotechnology in the past several decades, driven by advances in genetic modification technology (Fernandez-Cornejo and Caswell, 2006). We show that this induced growth in regions more ecologically similar to the US, especially for crops affected by GM advancements. Thus, the impact of local ecology on productivity changes over time as the focus of innovation shifts.

Quantification. We combine our empirical estimates with the model to quantify their aggregate productivity consequences. We calibrate the model to match our estimates of the effect of CPP mismatch on production and external estimates of the elasticities of supply and demand, which discipline crop choice and general-equilibrium interactions.

To benchmark the importance of inappropriate technology, we first study an intentionally extreme scenario of eliminating the gap between research on "leader" and "non-leader" environments. Comparing the observed equilibrium to this counterfactual, we estimate that inappropriateness reduces average global agricultural productivity by 58% and explains 15% of global productivity disparities measured by the inter-quartile range. This is because the countries most ecologically different from the frontier, especially in Africa and Asia, are also the least productive today.

We then study three counterfactual experiments that speak to contemporary trends. First, we identify the places where research investment could have the largest possible effect on global productivity after taking into account the network of environmental mismatch. We find large gains from focusing new research investments in India, China, and sub-Saharan Africa. Second, we measure the effects of the shift in global R&D toward large emerging economies: in particular, Brazil, Russia, India, and China (BRIC). The rise of BRIC is favorable for the world's least productive countries, due to their higher average environmental similarity to BRIC versus current technology leaders, and could serve as a partial substitute for local R&D in low-income countries. Finally, we study the consequences of a predicted poleward shift in the habitable range of CPPs due to climate change (Bebber et al., 2013). By exposing rich countries to CPPs that are currently only present in poor ones, climate change could coordinate international research on a more common set of threats and therefore, perhaps paradoxically, make some technologies more globally "appropriate."

Together, all three experiments convey that the global distribution of agricultural productivity—and even the broader notion of which environments are economically "good" and "bad"—is not an immutable object. Instead, this distribution is an endogenous outcome of innovation and its response to a changing world.

Related Literature. This paper builds on prior work about how the appropriateness of technology shapes productivity differences and technology diffusion (Griliches, 1957; Atkinson and Stiglitz, 1969; Stewart, 1978). Recent work in this area has modeled the productivity consequences of high-income countries' developing capital- or skill-complementing technology that is less appropriate elsewhere (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Wilson, 2004; Caselli and Coleman II, 2006; Rossi, 2022). We focus instead on ecological differences, which cause perhaps the most acute inappropriate technology problem since the underlying differences in endowments are (essentially) immutable. We also link causal estimates of the effect of inappropriateness on productivity to empirical analysis of the direction of innovation and technology diffusion.[2]

More broadly, this paper studies the causes and consequences of technology diffusion (Keller, 2004; Comin and Mestieri, 2014). Related work includes macro-level studies of technology transfer in prior centuries (Comin and Hobijn, 2004, 2010; Comin and Mestieri, 2018; Giorcelli, 2019) and micro-level studies of technology upgrading in modern times (e.g., Atkin et al., 2017; Verhoogen, 2021). A particularly related strand of this literature shows that constraints faced by farmers inhibit the adoption of modern agricultural technologies (e.g., Bandiera and Rasul, 2006; Conley and Udry, 2010; Duflo et al., 2011; Suri and Udry, 2022). While most work on these topics focuses on the characteristics of technology *adopters*, our results highlight how the *direction of innovation* shapes how broadly technologies diffuse and whether technological progress leads to more or less inequality. That is, our findings convey that the incentives faced by innovators—often living in a few high-income countries—are critical determinants of the global distribution of agricultural productivity.[3]

We also contribute to a large literature studying the determinants of the vast cross-country differences in agricultural productivity, which are larger even than those in manufacturing (Caselli, 2005). This work broadly concludes that differences in measurement, factor use, and geography

[2]Our analysis parallels work by Kremer and Glennerster (2004) and Hotez et al. (2007) on "neglected tropical diseases" for humans by studying "neglected ecological threats" for plants.

[3]Consistent with our hypothesis, Suri (2011) argues that differences in hybrid maize adoption in Kenya reflect variation in returns—a feature of the technology itself—and not adoption frictions. Marenya and Barrett (2009) also find that heterogeneous potential returns affect fertilizer demand in Kenya.

cannot fully account for these productivity gaps (e.g., Gollin et al., 2014; Adamopoulos and Restuccia, 2022; Boppart et al., 2023). Our work can be understood as showing how the uneven focus of technology can endogenously contribute to global disparities in productivity.

Finally, we extend a large literature on the relationship between environmental conditions and development (e.g., Kamarck, 1976; Bloom and Sachs, 1998; Gallup et al., 1999). Our focus on the confluence of ecology and technology diffusion is one mechanism in the theory of Diamond (1997), who argues that the easier diffusion of technology across "horizontal" landmasses explains the pre-modern development of Eurasia. Departing from prior work, our analysis emphasizes that the effect of geography is not fixed, but instead determined as an evolving outcome of endogenous technology development and diffusion.

Outline. This paper is organized as follows. Section 2 describes the model. Section 3 describes background, data, and measurement. Section 4 reports our results on the uneven focus of global innovation. Section 5 reports our results on technology diffusion. Section 6 reports our results on production. Section 7 presents our quantitative analysis. Section 8 concludes.

2. A Model of Inappropriate Technology in Agriculture

We first present a model that introduces the key economic mechanisms of the inappropriate technology hypothesis and our strategies for measurement and parameter identification.

2.1 Set-up

Production. This block of the model is intentionally standard (as in, e.g., Costinot et al., 2016). There is a set of countries indexed by $\ell \in \{1, \ldots, L\}$ and a set of crops indexed by $k \in \{1, \ldots, K\}$. In each country, there is a continuum of farms indexed by $i \in (0, 1)$. The output of farm i, if it produces crop k, is $\left(X_{i,k,\ell}\right)^{1-\gamma} (\theta_{k,\ell}\omega_{k,\ell}\varepsilon_{i,k,\ell})^{\gamma}$, where $X_{i,k,\ell}$ is the amount used of an agricultural input, $\theta_{k,\ell}$ is the productivity of that input, $\omega_{k,\ell}$ is the natural suitability for crop k in country ℓ, $\varepsilon_{i,k,\ell}$ is an idiosyncratic shock with a Fréchet distribution with mean one and shape parameter $\eta > 0$, and $\gamma \in (0, 1)$ measures the return to fixed factors. Each agricultural input, specialized to a crop k and country ℓ, is available at the price $q_{k,\ell}$.[4] Taking as given input prices, output prices, and productivity, each farmer i decides what crop to grow and how much to invest in inputs.

Environmentally Adapted Technology. There is a set of possible environmental features, $\mathcal{T} \subset \{0, 1, 2, \ldots\}$. The environment of each location-crop pair has features $\mathcal{T}_{k,\ell} \subseteq \mathcal{T}$, normalized to size $T > 0$. For example, $\mathcal{T}_{k,\ell}$ may encode the identities of locally present crop pests and pathogens (CPPs). Direct effects of these features can be modeled as part of productivity $\omega_{k,\ell}$.

Technologies have two characteristics that, together, determine their productivity in a given environment. The first is a "general" characteristic $A_k \in \mathbb{R}_+$, which affects productivity in any location. The second is a set of adaptations to specific ecological features, $(B_{t,k,\ell})_{t\in\mathcal{T}_{k,\ell}}$, which affect

[4] In Appendix A.5, we show how a production technology with additional inputs (e.g., fertilizer or labor) can be mapped to the baseline model after optimizing over the other choices.

productivity only when the relevant features are present. For example, if the input is an improved seed variety, each $B_{t,k,\ell}$ could describe the extent of resistance to a locally present CPP indexed by t. These components determine productivity $\theta_{k,\ell}$ as follows:

$$\theta_{k,\ell} = \exp\left(\alpha \log A_k + \frac{1-\alpha}{T} \sum_{t \in \mathcal{T}_{k,\ell}} \log B_{t,k,\ell}\right) \tag{1}$$

where $\alpha \in (0, 1)$ parameterizes the relative importance of the general characteristic.

The distinction between general and environmentally specific characteristics of agricultural technology can be illustrated via Reynolds and Borlaug's (2006) account of wheat development at the Centro Internacional de Mejoramiento de Maíz y Trigo (CIMMYT) in Mexico. An important breakthrough of CIMMYT scientists was to breed *semi-dwarf* wheat that grew shorter and were therefore able to sustain higher yields. In principle, this improvement was beneficial in any environment ("A"). A major challenge in globally deploying new semi-dwarf wheat varieties was that disease environments vastly differed: for example, the relatively dry, temperate environment of central Mexico is predominately affected by wheat rust, whereas the wet, tropical environment of West Africa is affected by a broader set of diseases including septorias, *Fusarium* blights, and barley yellow dwarf virus ("$\mathcal{T}$"). A major further focus of CIMMYT research was breeding resistance to these varied threats ("B"). Without these adaptations, there was no way to employ CIMMYT's improved varieties—and the embodied improvement of semi-dwarfism—in these environments.

Innovation. There is a representative innovator in country L, the technology "Leader." They can produce units of the technology at a constant marginal cost, normalized to 1. The innovator markets the technology in each country ℓ, but their market power is limited by a fringe of competitive "copycat" inventors that can replicate the technology at marginal cost $1 \leq C_\ell \leq \frac{1}{1-\gamma}$. The innovator also pays an iceberg cost $\rho_\ell \in [0, 1]$ on sales in country ℓ, which stands in for other costs of trade, licensing, and IP protection. Thus the innovator's profit per unit of technology sold is:

$$\mu_\ell := (1 - \rho_\ell)C_\ell - 1 \tag{2}$$

The innovator can make costly R&D investments to adapt their technology to each ecological characteristic. If the investment is made for crop k and characteristic t, then $B_{t,k,\ell} = \bar{B} \geq 1$ for all locations ℓ; otherwise, $B_{t,k,\ell} = \underline{B} = 1$. This investment has a fixed cost $\underline{c}$ if the characteristic is "local" to the Leader country, or $t \in \mathcal{T}_{k,L}$, and $\bar{c} \geq \underline{c}$ otherwise. The lower cost for directing research toward local characteristics may capture both knowledge about local conditions and physical inputs like local test fields and genetic material.

Equilibrium. To close the model, we assume that prices $(p_k)_{k=1}^K$ lie on a global demand curve $(p_k)_{k=1}^K = d((Y_k)_{k=1}^K)$, where Y_k is total production of each crop. An equilibrium is a vector of production $(Y_{k,\ell})$, total input demands $(X_{k,\ell})$, prices (p_k), and CPP technology development $(B_{t,k})$ such that (i) farmers optimize given correct conjectures of prices, (ii) innovators optimize given correct conjectures of prices, productivities, and local research, and (iii) markets clear for each crop.

Extended Model. Our model is intentionally simplified to ease exposition. In Appendix B, we present a version of the model generalized along five margins: (i) multiple countries can innovate, so leaders emerge endogenously; (ii) innovators can invest in both context-neutral ("A") and context-specific ("B") components of technology; (iii) innovators can improve these attributes along an intensive margin; (iv) innovators have imperfect expectations of technology demand; and (v) farmers face input-adoption wedges. We show how all results derived below apply to this case.

2.2 Model Predictions and Mapping to Estimation

We now describe the model's main predictions. The first three motivate our empirical strategies Sections 4-6. The last motivates our strategy for aggregation and quantification in Section 7. The proofs of all results are in Appendix A.

The Uneven Focus of Innovation. Three forces give the innovator incentives to direct research toward the ecological characteristics of the Leader country. First, it may be significantly cheaper to research local ecological characteristics versus non-local characteristics. As we further explain in Section 3.1.1, this is especially natural given the mechanics of plant development via selective breeding. Second, the Leader market could simply be a larger market: primitively, this could be driven by $\omega_{k,L} > \omega_{k,\ell'}$ for $\ell' \neq L$. Third, the leader market may have the largest profit margin, or $\mu_L > \mu_{\ell'}$ for all $\ell' \neq L$. This could arise due to better enforcement of intellectual property (IP) law in L. The case studied by Acemoglu and Zilibotti (2001), which attributes international disparities in innovation to heterogeneous IP enforcement, is nested when $\mu_\ell > 0$ if and only if $\ell = L$. Henceforth, we proceed under the simplifying assumption that, in equilibrium, technologies are developed *only* for the leader country: $B_{t,k,\ell} = \bar{B}$ if and only if $t \in \mathcal{T}_{k,L}$.

In Section 4, we present direct evidence that innovation is strongly focused on ecological characteristics of technology leaders. We moreover find support for all three proposed mechanisms: innovation targets markets that are rich (consistent with mechanism 2) and have effective IP protection (consistent with mechanism 3), but there is still a large residual "home bias" toward local conditions (consistent with mechanism 1). The remainder of our analysis relies *only* on this uneven focus of research and can be interpreted regardless of the mechanisms that drive it.

Mismatch and Technology Diffusion. Demand for technology is determined by farmers' profit maximization. For a farm i producing crop k, input demand is

$$X_{i,k,\ell} = (1-\gamma)^{\frac{1}{\gamma}} \theta_{k,\ell}\, \omega_{k,\ell}\, \varepsilon_{i,k,\ell}\, q_{k,\ell}^{-\frac{1}{\gamma}} \tag{3}$$

Farms demand more inputs when those inputs are well adapted to the local ecology (high $\theta_{k,\ell}$), when the farms are more productive (high $\omega_{k,\ell}$ or $\varepsilon_{i,k,\ell}$), and when the inputs are inexpensive (low $q_{k,\ell}$). Conditional on the appropriateness of technology, input choices differ from those chosen by a social planner *only* if the price of technology differs from the marginal social cost of producing it. In this sense, the model features no demand-side "frictions" inhibiting technology adoption.

Nonetheless, because farmers' input demand responds to the potential productivity of those inputs, technology use is systematically lower in markets for which technology is inappropriate. We define *ecological mismatch* with the leader as the fraction of k-characteristics that are not shared between location ℓ and L: $\delta_{k,\ell,L} := 1 - \frac{1}{T}|\mathcal{T}_{k,\ell} \cap \mathcal{T}_{k,L}|$. The following result describes how mismatch affects the total quantity of technology diffusion for crop k to country ℓ, $X_{k,\ell} = \int_{\ell-1}^{\ell} X_{k,i}\,\mathrm{d}i$:

Proposition 1. *Equilibrium technology diffusion from the Leader to country ℓ for crop k can be written as*

$$\log X_{k,\ell} = -\beta \cdot \delta_{k,\ell,L} + \chi_{k,\ell} + \chi_{k,L} + \chi_{\ell,L} \tag{4}$$

where the χ are additive effects, whose formulas are given in the Appendix, and $\beta \geq 0$, with equality if (i) technology is purely general-purpose ($\alpha = 1$) or (ii) innovation is evenly focused ($B_{t,k,\ell} = \bar{B}$ for all $t \in \mathcal{T}_{k,\ell}$).

In Section 5, we estimate an extended version of Equation 4 that includes multiple potential origin countries rather than one leader. This strategy makes it possible to include of origin-by-crop and destination-by-crop fixed effects, thus sweeping out possible threats to identification that relate to origin-market and destination-market characteristics. We explicitly derive this augmented estimating equation, as well as the interpretation of fixed effects and our identification strategy, in the extended model of Appendix B.

The prediction that mismatch inhibits technology diffusion relies on two properties: that technology is ecologically adapted and that innovation is unevenly focused. To test this mechanism in the data, we will check whether the effect of mismatch on technology diffusion is larger for innovation-intensive origin countries and crops. We will also test whether the effect is smaller for classes of technology that are less environmentally specific (e.g., harvesters versus improved seeds). We will finally test the model's prediction that the elasticity in Proposition 1 does not depend on destination characteristics such as income, productivity, and human capital: in the model, these characteristics affect the *level* of technology use but not its sensitivity to mismatch.

Mismatch and Agricultural Production. The model predicts that countries produce less of crops for which their local conditions are mismatched with those of the Leader:

Proposition 2. *Production of crop k in country ℓ, $Y_{k,\ell} > 0$, can be written as*

$$\log Y_{k,\ell} = -\beta \cdot \delta_{k,\ell,L} + \chi_k + \chi_\ell + \eta \log \omega_{k,\ell} \tag{5}$$

where $\beta \geq 0$, with equality if (i) technology is purely general-purpose ($\alpha = 1$) or (ii) innovation is evenly focused ($B_{t,k,\ell} = \bar{B}$ for all $t \in \mathcal{T}_{k,\ell}$).

In Section 6, we empirically estimate Equation 5. The crop and country fixed effects in the estimating equation respectively absorb prices and average local productivity, variables determined in equilibrium. The "residual," net of technology and these fixed effects, is a re-scaling of local innate productivity $\omega_{k,\ell}$. We leverage the identification assumption that observed ecological mismatch with the frontier is orthogonal to any *un*observed components of local productivity, conditional on two-way fixed effects and several strategies that proxy for observed dimensions of local productivity. We also introduce a dynamic strategy that differences out the residual $\omega_{k,\ell}$ over time and identifies the parameter β from plausibly exogenous changes in ecological mismatch.[5]

Inappropriate Technology and Productivity. We finally observe that, all else equal, countries that are more ecologically mismatched with the frontier are less productive:

Proposition 3. *Agricultural revenue per acre in country ℓ can be written as*

$$\log \Xi_\ell = \chi + \frac{1}{\eta} \log \left(\sum_{k=1}^{K} p_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} C_\ell^{-\eta \frac{1-\gamma}{\gamma}} A_k^{\alpha\eta} e^{-\beta \delta_{k,\ell,L}} \right) \tag{6}$$

where χ is a constant that does not depend on k or ℓ.

In Section 7, we will combine our empirical estimates with a calibration for external parameters to map out the consequences of inappropriate technology for the global distribution of agricultural productivity. In particular, to benchmark the effect of inappropriate technology, we study a case in which agricultural innovation counterfactually has a fully "even" focus: that is, innovators improve technology for all global ecological conditions. As we describe in more detail in Section 7.1, the model structure allows us to account for the equilibrium forces that are swept out in the "missing intercept" of our estimating equation.

3. Background and Measurement

In this section, we describe our measurement strategies. We begin with background information about crop pest and pathogen (CPP) targeting in biotechnology. We then describe our strategies for measuring CPP presence, ecological mismatch, agricultural technology development, technology diffusion, and agricultural production. We give summary statistics for all main variables in Table 1.

3.1 Local Agricultural Ecology: Crop Pests and Pathogens (CPPs)

3.1.1 Background: Pathogen Threats and Plant Breeding

CPPs—including viruses, bacteria, fungi, insects, and parasitic plants—are a dominant threat to agricultural productivity. Experts estimate that between 50-80% of global output is lost each year to CPP damage (Oerke and Dehne, 2004). In Brazil, for example, it is estimated that 38% of annual production is lost due only to insects, amounting to $2.2 billion in lost output per year (Bento, 1999). In the US, the Western Corn Rootworm alone caused $1 billion in annual losses prior to the development of transgenic corn (Gray et al., 2009). A critical focus of crop breeding, as a result, is developing resistance to damaging CPPs.

The oldest technique for breeding favorable plant traits such as CPP resistance is mass selection: saving the seeds of the "best" plants from a given cycle, re-planting them, and repeating the process

[5] In Appendix A.3, we also derive the model's predictions for physical yield and area. While boosting the productivity of a given crop expands production possibilities, it does not necessarily increase average yields for that crop *relative to other crops* due to the expansion of land onto less suitable land. We find evidence for these predictions in Section 6.

(McMullen, 1987, p. 41). This process naturally selects crop lineages with sufficient resistance to the local CPP environment. But resistance to *non-present* CPP threats is neither selected for nor likely to arise by chance mutation. Historically, adapting mass-selected crop lines to new environments has required substantial lineage-specific investment, like "shuttle breeding" alternative generations in different locations (see, e.g., Reynolds and Borlaug, 2006, pp. 8-9).

A more modern addition to the crop development toolkit is genetic modification. A significant portion of modern genetically modified (GM) technology focuses on conferring resistance to specific pests and pathogens (Vanderplank, 2012; Van Esse et al., 2020). In principle, direct access to a plant's genetic code side-steps the slow, localized process of natural selection in the field. But, due to both economic incentives and the continued necessity of field trials for both effectiveness and safety, GM technology has been used primarily for addressing CPP threats in high-income countries (Herrera-Estrella and Alvarez-Morales, 2001).

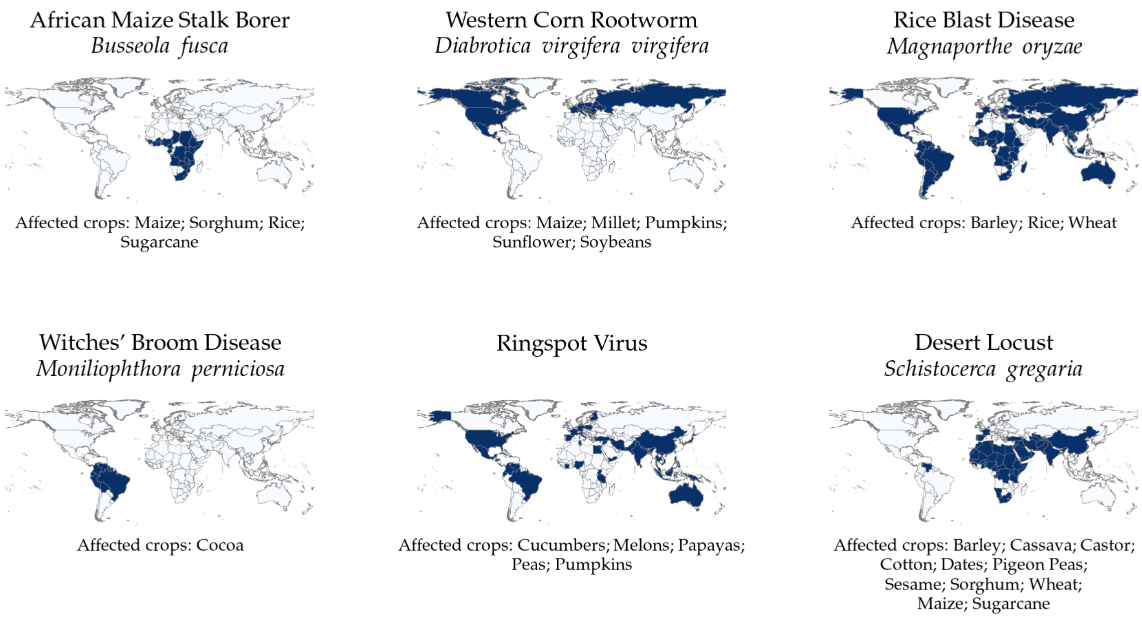
An illustrative case study of how modern plant varieties are locally targeted comes from Bt varieties, a prominent class of genetically modified plants. Bt varieties are engineered to express crystalline proteins, cry-toxins, that are naturally produced by *Bacillus thuringiensis* bacteria ("Bt") and destructive toward specific insect species. Cry toxins are insecticidal because they bind receptors on the epithelial lining of the intestine and prevent ion channel regulation. Due to the specificity of intestinal binding activity, cry toxins are highly insect-specific. This feature, while crucial for limiting the Bt varieties' broader ecological impact, makes their development highly targeted to specific pest threats. The main targets for early Bt corn varieties were the European Maize Borer and Corn Rootworm (Munkvold and Hellmich, 1999), major threats in the US and Europe that are not present elsewhere in the world. δ-endotoxins were originally identified as candidate toxins specifically because of their effectiveness against these pests (Galitsky et al., 2001; Bessin, 2019).

3.1.2 Measuring Pests and Pathogens: The Crop Protection Compendium

Our main strategy for measurement and identification is based on systematically measuring global differences in CPP environments. For this, we use data from the Centre for Agriculture and Bioscience International's (CABI) Crop Protection Compendium (CPC), self-described as the "world's most comprehensive site for information on crop pests." Construction of the database began in the 1990s as a collaboration between CABI, the UN Food and Agriculture Organization (FAO), and the Technical Centre for Agricultural and Rural Cooperation, with the goal of assisting agricultural research and CPP control and with a particular focus on being globally representative. The CPC was compiled through extensive searches of existing research, including the 460,000 research abstracts in the CABI database, as well as contributions from a range of governmental and international organizations, including the World Bank, the FAO, the United States Department of Agriculture, and the Consultative Group on International Agricultural Research (Pasiecznik et al., 2005). In total, we compile information on 4,951 plant pests and pathogens.

For each species, the CPC includes a datasheet from which we extract two key pieces of information. First, the datasheet reports the CPP's global geographic distribution. Figure 1 displays the

Figure 1: Data on Example CPPs



Notes: These maps visualize our data on crop pest and pathogen (CPP) presence and affected crops from the CABI Crop Protection Compendium (CPC). Blue shading denotes the countries in which a CPP is present. The list of affected crops is constructed by intersecting the dataset's master list of host plants with our list of major agricultural crops.

distribution map for six pests, including the Maize Stalk Borer and Western Corn Rootworm, which were referenced in previous examples.

Second, the datasheet reports all the host species that each pest or pathogen affects. For example, CABI reports that the African Maize Stalk Borer harms maize, sorghum, rice, and sugarcane, while the Western Corn Rootworm harms maize, millet, pumpkins, sunflower, and soybeans (Figure 1, top panel). Our data contain information on 132 hosts that we can link to our subsequent analyses of technology development, technology transfer, and production.

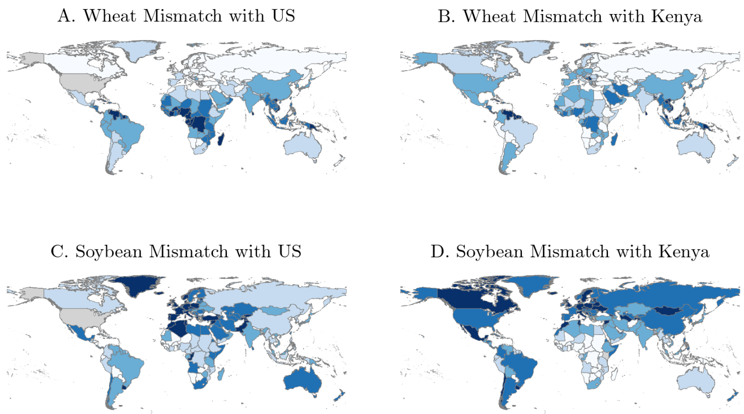
3.1.3 Measuring Inappropriateness: Crop Pest and Pathogen Mismatch

We next describe our main measure of inappropriateness: *CPP mismatch*. Using our lists of locally present CPPs affecting crop k in each location ℓ or ℓ', we compute the following measure of CPP mismatch at the location-pair-by-crop level:

$$\text{CPP Mismatch}_{k,\ell,\ell'} = 1 - \frac{\text{Number of Common CPPs}_{k,\ell,\ell'}}{\left(\text{Number of CPPs}_{k,\ell} \times \text{Number of CPPs}_{k,\ell'}\right)^{1/2}} \tag{7}$$

The measure, which has the form of one minus a correlation or cosine similarity, equals zero when ℓ and ℓ' have all the same CPPs for crop k and equals one when ℓ and ℓ' have no CPPs in common for crop k. As discussed by Jost et al. (2011), the measure defined by Equation 7 is one of several standard divergence measures in ecological sciences that satisfy basic properties of *density invariance*,

Figure 2: Illustrating the Variation in CPP Mismatch



Notes: Each map shows the distribution of CPP Mismatch$_{k,\ell,\ell'}$ across countries ℓ' fixing the indicated crop k and reference country ℓ and demeaned at the country ℓ' and crop k levels. Darker shades of blue indicate higher values (i.e., more different crop pest and pathogen environments), coded into five quantiles.

replication invariance, and *monotonicity*.[6]

CPP mismatch varies at both the country-pair level, fixing crops, and the crop level, fixing country pairs. The *country-level variation* is illustrated Figure 1: different countries are endowed with different CPPs. The *crop-level variation* is due to the fact that each CPP only affects a particular set of plant species. Depending on the identity of each country's locally present CPPs, a single pair of countries will have different values of CPP mismatch for each crop. These two sources of variation allow us to fully absorb any differences across countries or crops in our analysis.

To illustrate the key identifying variation, Figure 2 visualizes the distribution of mismatch with the US and Kenya for wheat and soybeans. There are substantial differences across crops and countries. For example, the US has much lower mismatch with parts of Western Europe for wheat than for soybeans, but much higher mismatch with parts of Central and West Africa for wheat than for soybeans. While much of South America has intermediate mismatch with the US for both crops, mismatch with Kenya is very low for wheat but very high for soybeans. Throughout the analysis, we only use this variation *within* both countries and crops.

3.1.4 Addressing Threats to Interpretation

In our main empirical analysis, we will use CPP mismatch as a plausibly exogenous shifter of the appropriateness of technology for crop k developed for the ecology of country ℓ' and used in country ℓ. As a result, a natural question is what forces drive the geographic distribution of CPPs, which

[6] One leading alternative commonly used by ecologists is the Jaccard distance, which equals the ratio of non-shared species to total unique species across the two environments. Results for all subsequent analyses are essentially identical under this alternative measure.

ultimately underlies the identifying variation described above.

The determinants of the cross-sectional distribution of each CPP, according to ecologists, depend on "numerous [and] sometimes idiosyncratic" factors (see Bebber et al., 2014; Shaw and Osborne, 2011, for greater detail). While features of the environment, most prominently temperature, affect CPP presence, they often have limited predictive power and CPPs are often absent in ecologically habitable areas. Moreover, by our own measurement, CPP mismatch is not strongly correlated with measures of mismatch in a range of other geographic and ecological characteristics (see Table A1 and Section C). Bebber et al. (2014) also document that CPP distributions measured from the CABI CPC appear unrelated to patterns of trade, travel, or tourism, suggesting that agricultural activity plays a limited role in shaping broad patterns in the cross-sectional distribution of CPPs. Since most CPPs have non-agricultural host plants, for most species there is not a clear link between changes in human activity and changes in presence.

Nevertheless, we use two additional strategies to fully purge our measure of inappropriateness of any potential consequences of human activity.

Removing Eradications and Invasive Species. We use additional data from CABI to study the possible role of eradications and species invasions—two ways in which humans *may* affect the range of individual CPPs—and develop a measure of CPP mismatch purged of both sources of variation. First, CABI reports not only whether a CPP is currently present in a country, but also whether it *has ever been* present. We therefore calculate a variant of CPP mismatch that includes eradicated CPPs. It is worth noting that such eradication events are extremely rare. The number of CPP-country-crop triads increases by under 3% when using the eradication-robust CPP presence classification. Second, to investigate the potential role of invasive species, we use the CABI Invasive Species Compendium (ISC) to identify all invasive and high-invasive-potential CPPs. We calculate a second variant of mismatch that excludes all of these species.[7]

Predetermined Agro-Climatic Mismatch. We also investigate the importance of differences in other environmental characteristics, like temperature, rainfall, and soil composition. Appendix C introduces an independent strategy to measure *agro-climatic mismatch* and reports our main empirical results using agro-climatic mismatch as an additional determinant of inappropriateness. Replicating our main findings using the mismatch of pre-determined geographic characteristics builds confidence that our main results are not driven by idiosyncrasies of CPPs or their measurement, including any potential effect of human activity on CPP distributions.

3.2 Technology Development and Diffusion

3.2.1 The UPOV Plant Variety Database

Our first strategy to measure technology diffusion is based on a novel dataset of all global instances of intellectual property for crop varieties. We obtained these data from The International Union for

[7]The ISC identifies 748 CPPs, or about 15% of our original list, as potentially invasive based on surveys of existing literature. We view our approach of dropping potentially invasive CPPs altogether as conservative, because it does not rely on information about exactly where a CPP is (recently) invasive rather than native.

the Protection of New Varieties of Plants (UPOV), the inter-governmental organization that designs and administers systems of intellectual property protection for plant varieties around the world. These data cover all UPOV member states, including most of North and South America, Europe, West Africa, and East Asia.[8]

The data are a comprehensive record of all plant variety certificates in UPOV member countries. A plant variety certificate is an internationally standardized form of intellectual property protection that is distinct from patent protection and exists in many countries that do not recognize patents for seeds, plant parts, or other biological technologies. To be recognized by UPOV, a variety must be "DUS": Distinct from others, Uniform for plants within a generation, and Stable for plants across generations.[9] Since these characteristics are relatively straightforward to document, legal barriers to obtaining protection are limited. This helps ensure that the UPOV database captures almost all commercially relevant plant varieties, including those that are developed by small-scale and/or public-sector breeders instead of large, private-sector firms. Finally, a breeder must protect a variety separately in each country where they want legal enforcement. Thus, observing that a variety is protected in a particular country is a strong indication that the variety was marketed and sold there.

For each certificate, we observe the date of issuance, the country of issuance, the plant species, and a unique "denomination" identifier associated with the variety. The UPOV Convention of 1991 stipulates that the denomination of a specific plant variety must be consistent across member countries, allowing us to see the appearance of a single plant variety in multiple countries. The data, when linked to a list of major crops, consists of 458,034 total variety certificates and 236,529 unique denominations, spanning 62 countries and 109 crops.

We define technology development and technology transfer as follows. For every unique denomination in the data, we define the country of its first appearance as the origin country, since this is likely to be the market for which the variety was first developed.[10] This allows us to measure the number of unique seed varieties developed for each crop and each country during the sample period ("technology development"). We then count, in any given time period, the number of varieties of each k, newly registered in country ℓ, and originating from country ℓ' ("technology diffusion"). For our main analysis, we focus on a static cross-section and sum over all final registrations after 2000. About 30% of all denominations, and 46% of denominations that originate in crop-specific "leaders" that register the most varieties, are transferred to at least one other country (Figure A1).

Plant varieties are an appealing measure of "technology" in our study for three reasons. First, they have a clear role in the production process: plant varieties are the "final products" that embody key ideas and productive traits, like the aforementioned examples of semi-dwarfism or (selectively bred or genetically introduced) pest resistance. Second, the (un)availability of plant varieties is a

[8]For the full list of member countries, see https://www.upov.int/members/en/.

[9]To establish DUS, the applicant is required to conduct field trials to assess all three requirements, collecting data on the variety's characteristics, uniformity, and stability. In the US, for example, which follows UPOV guidelines exactly, there must be data from at least two trials, which can be conducted in the same year in different locations or in different years in the same location (see https://www.ams.usda.gov/services/plant-variety-protection/dus-guidelines).

[10]This avoids potential issues with using the country of the firm headquarters. For example, while Monsanto was headquartered in the US during our sample period, it invested substantially in developing soybean technology tailored to the Brazilian market.

Table 1: Summary Statistics

Variable Name	Mean	Standard Deviation
Panel A: Ecological Mismatch (Country-Pair-Crop Sample)		
CPP Mismatch	0.433	0.169
CPP Mismatch, Excluding Eradications	0.422	0.168
CPP Mismatch, Excluding Invasive Species	0.460	0.185
Agro-Climatic Mismatch	0.915	0.437
Panel B: Technology Transfer (Country-Pair-Crop Sample)		
Any Variety Transfer (0/1)	0.035	0.183
Total Variety Transfers (Top-Coded)	0.224	2.473
log Total Variety Transfers	1.066	1.153
Any Patent Transfer (0/1)	0.014	0.119
Total Patent Transfers (Top-Coded)	0.133	2.208
log Total Patent Transfers	1.254	1.402
Any Patent Citations (0/1)	0.002	0.045
Total Patent Citations (Top-Coded)	0.009	0.369
log Total Patent Citations	0.887	1.161
Panel C: Ecological Mismatch (Country-Crop Sample)		
CPP Mismatch with the Crop-Specific Leaders	0.428	0.185
CPP Mismatch '', Excluding Eradications	0.414	0.179
CPP Mismatch '', Excluding Invasive Species	0.459	0.196
CPP Mismatch with the US	0.428	0.172
Agro-Climatic Mismatch with the Crop-Specific Leaders	0.428	0.172
Agro-Climatic Mismatch with the US	0.866	0.344
CPP Mismatch with Green Revolution Breeeding Centers	0.460	0.136
Panel C: Output (Country-Crop Sample)		
log Output	9.859	3.050
Change in log Output, 1960-1980 (Green Revolution)	0.477	0.990

Notes: This table reports summary statistics for the main variables used in our empirical analysis. The variable name is reported in the leftmost column, followed by its mean and standard deviation. In Panel A, we report statistics for our main measures of ecological mismatch used in our analysis of technology transfer at the country-pair-crop level. In Panel B, we report statistics for our main measures of technology transfer, also measured at the country-pair-crop level. In Panel C, we report statistics for our main measures of ecological mismatch for our analysis of agricultural output, measured at the country-crop level. Finally, in Panel D, we report statistics for our main meaures of agricultural output and output change, measured at the country-crop level.

primary concern for policymakers (e.g., Walker and Alwang, 2015; Access to Seeds Foundation, 2019) and an object of interest in many past studies of agricultural technology diffusion (e.g., Griliches, 1957; Evenson and Gollin, 2003a). Third, the ability to precisely link varieties with different plant species (crops) and locations will aid in our identification strategy. Nonetheless, plant varieties are only one part of the broader landscape of agricultural technology. Our second measurement strategy helps fill this gap.

3.2.2 Global Patent Data

As a second measurement strategy, we compile data on all global patents and patent families related to agricultural technology from the *PatSnap* database. We define the set of agricultural patents as all patents falling into Cooperative Patent Classification (CPC) class A01.

We use each patent's title, abstract, and CPC class to classify patents by topic. First, we link each patent to zero, one, or multiple crops in our data by searching for each crop's scientific and common name in each patent title and abstract. Unlike plant varieties, the link between each technology and individual crops is less straightforward and a single patent may apply to multiple crops or not be explicitly about any crop (e.g., if it is related to soil modification or general purpose mechanical technology). Second, we link each patent to CPPs by searching for each CPP scientific name in each title and abstract. Directly measuring technology development across CPPs was not possible in the UPOV data and is a key advantage to the additional information in the patent data. Finally, we group patents by type of technology using the CPC class information. In particular, we divide patents between those that are biological or chemical technologies—for which we expect local ecology to matter—and those that are mechanical technologies—for which we do not.

We measure technology transfer in the patent data using two complementary strategies. Our first strategy defines the first issued patent in each family as the focal patent and all subsequently filed patents that are part of the same families as international transfers of the original technology. This approach, familiar from the literature on cross-border patenting (e.g., Dechezleprêtre et al., 2011) and also conceptually consistent with our definition of variety transfer, measures when the *same* invention diffuses across countries. Our second strategy counts the number of (crop-specific) agricultural patents in a destination that cite agricultural patents from a given origin. This approach, familiar in the literature on geographic spillovers of innovation (e.g., Jaffe et al., 1993; Liu and Ma, 2023), measures the diffusion of knowledge that underlies potential follow-on innovation.

3.3 Agricultural Outcomes

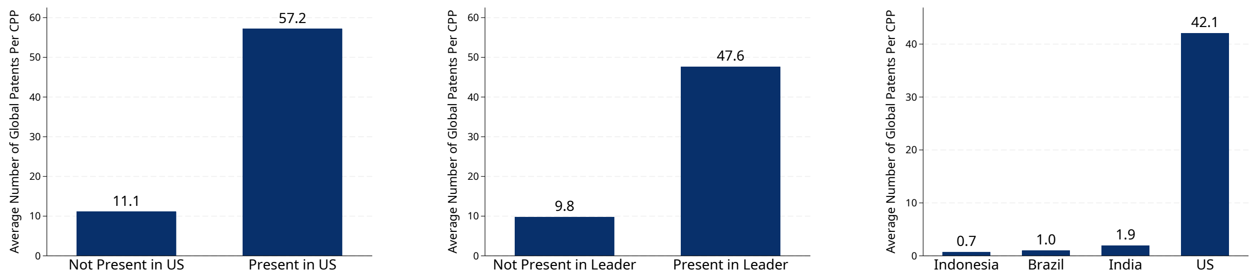
We take data on agricultural output, harvested areas, and yields across crops and countries from the UN Food and Agriculture Organization (FAO) statistics database. These data are compiled from national statistical agencies in each country as well as reports on agricultural production that all FAO member states are required to submit. The data are then cross-referenced and supplemented using information from international organizations (e.g., the World Bank, the International Food Policy Research Institute) and commercial data providers.

We also compile data on the maximum potential yield of each crop in each country according to agronomic models produced by the FAO Global Agro-Ecological Zones (GAEZ) database. FAO GAEZ uses local geographic and climatic conditions to determine the suitability of each field of land for growing each crop, and converts this into a measure of "potential output" in physical units. We aggregate these field-level data to construct a country-by-crop level measure that captures output differences that are explainable by variation in geography.

To study agricultural output across regions *within* countries, we compile sub-national agricultural output data from the latest national agricultural census for both Brazil and India. These are the two developing countries for which CABI reports sub-national CPP distribution information, making it possible to study the impact of technology mismatch at the sub-national level. The Brazilian data are from the 2017 round of the Censo Agropecuário and cover 49 crops. The Indian data are from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) Database, constructed from the 2015 Agricultural census, and cover 20 states and 20 crops. We also construct a potential yield control variable from the FAO GAEZ data at the level of crop-state pairs for this analysis.

Figure 3: Global Patenting Related to CPPs

(a) Patents by Presence in US **(b)** Patents by Presence in Any Leader **(c)** Patents for Single-Country CPPs



Notes: Panel (a) reports the average number of patented technologies developed about CPPs that are and are not present in the United States. Panel (b) reports the average number of patented technologies developed about CPPs that are and are not present in the most common *leader* countries in our dataset (the United States, France, the Netherlands, Japan, Russia, Spain, and Argentina). Panel (c) reports the number of patented technologies developed about CPPs that are present only in (i.e., endemic to) Indonesia (42 CPPs), Brazil (49 CPPs), India (69 CPPs), and the United States (73 CPPs).

4. The Uneven Focus of Innovation

In this section, we document that global agricultural research is strongly focused on the ecological characteristics of a few R&D "leaders." We first show this pattern in the raw agricultural patenting data. We next use cross-sectional data to show how market size, the extent of intellectual property protection, and local focus contribute to this phenomenon.

4.1 Innovation Disparities in the Raw Data

The patent data confirm that crop pests and pathogens command significant attention in agricultural technology development. In particular, 60% of all patents related to agriculture mention at least one CPP by its scientific name.

However, not every pest and pathogen gets equal attention in patented research. We illustrate this point with a few simple comparisons in the raw data. Figure 3a shows that CPPs present in the United States, like the corn rootworm in our introductory example, are on average mentioned in more than five times as many patents as CPPs only present outside the United States, like the African maize stalk borer in our introductory example. A comparable disparity emerges if we expand our focus to a larger set of seven technological "leaders" that are most active in our data on variety registrations (Figure 3b). Figure 3c illustrates this point more dramatically by restricting attention to CPPs that are *only* present in each of four large agricultural economies: the United States, India, Brazil, and Indonesia. A relatively large number of CPPs are present only in each of these countries: 73 in the US, 69 in India, 49 in Brazil, and 42 in Indonesia. While each of the CPPs present only in the US has received an average of 42.1 patents, the average in the other countries are all below 2.

Table 2: The Direction of Innovation Across CPPs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Technology Development (0/1)				log Technology Development			
Local CPP presence (0/1)	0.0668	0.0575	0.0454	0.0479	0.2281	0.2329	0.0988	0.1807
	(0.0134)	(0.0114)	(0.0096)	(0.0105)	(0.0819)	(0.0714)	(0.0620)	(0.0664)
Global CPP presence (log area weighted)		0.0035	0.0004			0.0312	-0.0186	
		(0.0007)	(0.0002)			(0.0250)	(0.0167)	
Global CPP presence (IP weighted)			0.0014				0.0181	
			(0.0003)				(0.0040)	
Global CPP presence (log GDP weighted)			0.0003				-0.0214	
			(0.0003)				(0.0230)	
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPP Fixed Effects	No	No	No	Yes	No	No	No	Yes
Observations	492,422	428,400	428,400	492,422	9,082	8,795	8,795	8,557
R-squared	0.136	0.149	0.154	0.202	0.239	0.243	0.252	0.557

Notes: The unit of observation is a country-CPP pair. In columns 1-4, the outcome variable is an indicator that equals one if there is any patent related to the CPP by an inventor in the country, and in columns 5-8 it is the log number of patents related to the CPP by an inventor in the country. CPPs related to each patent were determined by searching for each CPP scientific name in the titles and abstracts of all patents related to agricultural technology. Country fixed effects are included in all specifications and CPP fixed effects are included in columns 4 and 8. Standard errors are clustered by country.

4.2 Disparities are Driven by Local Focus, Market Size, and IP Protection

The focus of innovation on the CPP threats in R&D leaders could be driven by three primary mechanisms, all of which were embedded in the model (Section 2.2): (i) the lower cost of doing agricultural research on local characteristics, (ii) the greater revenue opportunity in larger markets, and (iii) the greater revenue opportunity in markets with more effective intellectual property protection. We now use cross-sectional data on patents across countries and CPPs to test for each of these mechanisms.

To do so, we estimate the following regression model across countries ℓ and CPPs p:

$$y_{\ell,p} = \beta \cdot \text{Local}_{\ell,p} + \gamma \cdot \text{RevenueOpportunity}_p + \delta_\ell + \varepsilon_{\ell,p} \tag{8}$$

where $y_{\ell,p}$ is a measure of patenting activity related to CPP p by inventors in country ℓ. The inclusion of country fixed effects (δ_ℓ) allows us to absorb any unobservables that may affect the simple comparison of means in Figure 3, like different propensities to patent technologies conditional on developing them. $\text{Local}_{\ell,p}$ is an indicator that equals one if CPP p is present in country ℓ. $\text{RevenueOpportunity}_p$ includes several proxies for the potential effect of global CPP-level market size, including the number of countries affected by each CPP as well as the income-weighted and intellectual property protection-weighted number of countries affected by each CPP.

Our estimates in Table 2 suggest that all three proposed mechanisms play a role. In the first four columns, the outcome variable is an indicator variable for any patenting activity. In column 1, we only include $\text{Local}_{\ell,p}$ as a regressor (along with the fixed effects) and find that $\beta > 0$. Thus, innovation is disproportionately focused on CPP threats that are present in local markets. We next find that innovation is directed toward CPPs with larger global market size (columns 2-3), but this is only true when those markets enforce IP protection (column 3). Finally, in column 4 we estimate an augmented version of Equation 8 that also includes CPP fixed effects, thus fully absorbing any unobservables at the CPP level including (but not limited to) revenue opportunities. We find a quantitatively similar coefficient on local presence, suggesting it has a large effect even conditional on all CPP-level characteristics. In columns 5-8, we study the intensive margin of innovation by replicating the analysis with the log number of patents as the outcome. While the sample size declines substantially due to the number of zeroes in the data, the broad findings are similar. In the most conservative specification (column 8), the local presence of a CPP increases patenting related to that CPP by nearly 20%.

In Table A2, we conduct a similar analysis using our global variety protection data to study the uneven focus of innovation across *crops* that grow in different environments. As above, we find evidence of a global focus on crops produced in IP-protecting countries and, on top of this, a significant local focus on locally produced crops that remains positive, large, and significant after the inclusion of crop and country fixed effects.

Taken together, these results validate that agricultural innovation focuses on the environmental conditions of R&D leaders and suggest that market size, intellectual property protection, and local focus all contribute toward this phenomenon. Having established this premise, we next study the implications of this uneven focus on technology diffusion, specialization, and productivity.

5. Mismatch and Technology Diffusion

In this section, we study the relationship between ecological mismatch and technology diffusion. We find that mismatch lowers cross-border technology diffusion, measured by variety introduction, patenting, and patent citations. This effect is an order of magnitude stronger for diffusion from R&D "leaders," identified by their contribution to technology development in the data, and not significantly mediated by the income, human capital, or agricultural-input-intensity of destination countries. In additional analysis, we show that mismatch predicts lower technology access in modern and historical contexts that lack IP protection. Together, these findings are consistent with a model of inappropriate technology shaping international technology diffusion.

5.1 Empirical Strategy

We estimate the following model at the level of crops k, origin countries ℓ', and destination countries ℓ:

$$\text{Technology Diffusion}_{k,\ell',\ell} = \beta \cdot \text{CPP Mismatch}_{k,\ell',\ell} + \chi_{\ell,\ell'} + \chi_{k,\ell} + \chi_{k,\ell'} + \varepsilon_{k,\ell,\ell'} \tag{9}$$

The model includes two-way fixed effects at the origin-by-destination, crop-by-origin, and crop-by-destination levels. Standard errors are double-clustered by origin and destination.

Our hypothesis is that $\beta < 0$, or that ecological mismatch depresses technology diffusion. We may find no effect, however, if ecological adaptations are not an important determinant of technologies' effectiveness or if demand for technology is relatively inelastic to its effectiveness.

The two-way fixed effects empirical design, equivalent to a "triple difference" across crops, origins, and destinations, allows us to nonparametrically control for confounding factors that affect the supply and demand of agricultural technologies. These factors are spelled out in our derivation of the estimating equation in the model (Proposition 1). Crop-by-origin fixed effects control for R&D intensity in the origin country. Crop-by-destination fixed effects control for current or future market opportunities for innovators, abundance of complementary inputs, and potential barriers to technology adoption. Origin-by-destination fixed effects absorb bilateral trade costs and distance, which could affect the transfer of all products or ideas. The residual therefore captures measurement error as well as unobserved, stochastic components of technology demand.

Any possible confounder that biases our estimates must therefore vary at the *crop-by-origin-by-destination* level and be correlated with the (residual variation) in mismatch. To illustrate this, consider the possibility that innovators anticipate high technology demand in market for crop k in country ℓ. If this is common across innovators in all origin markets, then this is fully absorbed by the fixed effects in Equation 9. If it is idiosyncratic to innovators in a given origin market ℓ', then it may threaten identification, but only insofar as it is spuriously correlated with CPP mismatch.

To guard against any remaining potential confounders, we pursue two additional strategies. First, we estimate versions of Equation 9 that interact CPP Mismatch with proxies for the innovation intensity of origin countries and crops. Our model predicts that mismatch inhibits diffusion to a greater extent from technological leaders. Thus, to explain our main result, any confounding factor would *additionally* need to be systematically more pronounced for observations in which the origin is a crop-specific technology leader. Second, we exploit an additional difference across types of technology. In particular, we estimate how mismatch separately affects the diffusion of biological technologies, whose productivity we expect to depend on environmental conditions, and mechanical technologies, whose productivity we expect to be less affected by the environment.

5.2 Ecological Mismatch Reduces Technology Diffusion

We find that CPP mismatch significantly inhibits the international flow of agricultural biotechnology. We first show this result using our novel data on variety transfers (Panel A of Table 3). In column 1, the outcome is an indicator that equals one if any transfer has taken place (extensive margin), using the full sample of crops and country pairs. In column 2, the outcome is the total number of variety transfers (top-coded to limit the influence of extreme observations) and in column 3, it is the log of the number of technology transfers, isolating the intensive margin effect. The estimate from column 3 implies that CPP mismatch inhibits 30% of international technology transfer for the median in-sample level of CPP mismatch. These results suggest that mismatch lowers the availability of improved agricultural inputs, the products through which farmers can access advancements in agricultural technology. These findings also connect to our motivating anecdotes of plant varieties whose usefulness is restricted to specific pest and pathogen environments.

Turning to the patent data, we find that ecological mismatch also reduces patent transfers (Panel

Table 3: CPP Mismatch Inhibits International Technology Transfer

	(1)	(2)	(3)
	Any Transfer (0/1)	Total Transfer (Top-coded)	log Total Transfer
	Panel A: Crop Variety Transfers		
CPP Mismatch (0-1)	-0.0275	-0.3148	-1.2018
	(0.0106)	(0.1153)	(0.3861)
Observations	204,287	5,791	5,687,379
R-squared	0.383	0.797	0.625
	Panel B: Patented Technology Transfers		
CPP Mismatch (0-1)	-0.0072	-0.1122	-0.0828
	(0.0017)	(0.0424)	(0.0362)
Observations	5,661,392	5,661,392	80,210
R-squared	0.6254	0.6775	0.9386
	Panel C: Patented Technology Citations		
CPP Mismatch (0-1)	-0.0015	-0.0075	-0.0379
	(0.0006)	(0.0040)	(0.1328)
Observations	5,661,392	5,661,392	10,156
R-squared	0.5167	0.5737	0.9332
Crop-by-Origin Fixed Effects	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes
Origin-by-Destination Fixed Effects	Yes	Yes	Yes

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. In Panel A, the outcome variable is constructed using variety transfer data from the UPOV database; in Panel B, it is constructed from patent tranfer data using patent family information; and in Panel C, it is constructed from patent citation data using the full citation network of all patented agricultural technologies. CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. In column 1, the outcome is an indicator for any transfer; in column 2, it is the total number of transfers, top-coded at the 95th percentile; and in column 3, it is the log of the number of transfers. Standard errors are double-clustered by origin and destination.

B). This verifies our core finding that mismatch inhibits technology transfer in a second, independent dataset. Moreover, because patents "un-bundle" the separate innovations (e.g., specific genetic improvements) that might underlie a seed variety brought to market, our second finding captures a qualitatively different aspect of technology transfer than our first.

We finally find that ecological mismatch significantly reduces cross-country patent citations (Panel C). These findings suggest that the underlying ideas embodied in agricultural patents are less applicable in mismatched settings, consistent with our previous finding that the content of those patents is highly specialized to local conditions (Section 4). Moreover, in contrast to our findings for variety and patent transfer, our findings for patent citations directly show that mismatch affects the conditions for local *follow-on* innovation: inventors in markets that are highly mismatched from the rest of the world have less relevant international knowledge to build on.

Breaking Down Results by Type of Inventor. In principle, these baseline estimates could be driven by private-sector innovation, public-sector innovation, or both. According to the model, it would depend on the extent to which each type of innovation is more focused on local ecological conditions (increasing the absolute value of β) versus more spread out across global ecological conditions (reducing the absolute value of β). To study this, we leverage the fact that our micro-data on both varieties and patents record the name of the applicant. We classify all applicants as either private firms or non-private entities (i.e., public sector institutions or universities) and estimate Equation 9 separately for the transfer of private sector and non-private sector technologies.[11]

The estimates are reported in Table A3. We find similar effects for both private and non-private technologies. This suggests that both sets of innovators develop locally-tailored technologies, albeit potentially for different reasons. One hypothesis is that the private sector may be more responsive to profit incentives, while the public sector may have a specific national research mandate. A fuller exploration of the intersection between the inappropriate technology hypothesis and the different parts of the research ecosystem is an important area for additional work.

5.3 Testing the Inappropriate Technology Mechanism

So far, our estimates of Equation 9 capture the average effect of CPP mismatch across all origin markets, destination markets, and crops. Our model, however, implies that ecological mismatch with foreign markets matters only insofar as those markets are the focus of R&D investment. That is, our baseline estimates should be driven by ecological mismatch with the most innovative origin markets (the "technology leader" from the model) and by crops that are the focus of the most global innovation. Ecological mismatch with markets that were are not the focus of R&D in the first place should have little effect on technology diffusion. Moreover, our model also predicts that this should hold *regardless* of the abundance or scarcity of other inputs like physical or human capital. While these destination-level characteristics likely affect the *level* of technology transfer, they do not affect the appropriateness of technology across markets, which is an outcome of innovation incentives in technology-leader countries. We now test these predictions in the data.

Mismatch with the Frontier Matters Most. To study the effects of mismatch from the R&D leader, we estimate versions of the following augmented version of (9) that parameterizes heterogeneity in the effect of CPP mismatch:

$$y_{k,\ell',\ell} = \beta^{NL} \cdot \text{CPPMismatch}_{k,\ell',\ell} + \beta^{L} \cdot L_{k,\ell'} \cdot \text{CPPMismatch}_{k,\ell',\ell} + \chi_{\ell,\ell'} + \chi_{k,\ell} + \chi_{k,\ell'} + \varepsilon_{k,\ell,\ell'} \tag{10}$$

where $L_{k,\ell'}$ is an indicator variable that equals one for the countries ℓ' that we identify as the leader countries for crop k. We have two strategies for defining $L_{k,\ell'}$. The first is to treat the US as the frontier for all crops, or set $L_{k,\ell'} = \mathbb{I}[\ell' = \text{US}]$. This is motivated by the United States' pre-eminence

[11] We made this classification by feeding all applicants through the GPT-4o model with a prompt that included examples of each organization type. When merged to our data set for analysis at the country-pair-by-crop level, roughly three times as many observations have at least one private compared to at least one non-private technology transfer (8,300 vs. 2,600 in the variety transfer data and 78,000 vs. 26,000 in the patent transfer data). Thus, non-private technology represents a smaller but substantial share of the transfer variation.

Table 4: CPP Mismatch with Leader Countries and Technology Transfer

	(1)	(2)	(3)	(4)
	Dependent Variable is Any Technology Transfer (0/1)			
Leader defined as:	United States	Top Variety Developer	Top 2 Variety Developers	Top 3 Variety Developers
CPP Mismatch (0-1)	-0.0241	-0.0229	-0.0181	-0.0136
	(0.0096)	(0.0099)	(0.0092)	(0.0088)
CPP Mismatch (0-1) x Leader (0/1)	-0.2539	-0.3319	-0.3426	-0.3215
	(0.0142)	(0.0699)	(0.0623)	(0.0535)
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	Yes
Country Pair Fixed Effects	Yes	Yes	Yes	Yes
Observations	204,287	204,287	204,287	204,287
R-squared	0.3830	0.3840	0.3850	0.3854

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. The outcome variable is an indicator that equals one if any variety transfer has taken place. CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. Each regression also includes an interaction between CPP mismatch and an indicator that equals one if the origin is a leader country, for different definitions of the leader country (noted at the top of each column). Standard errors are double-clustered by origin and destination.

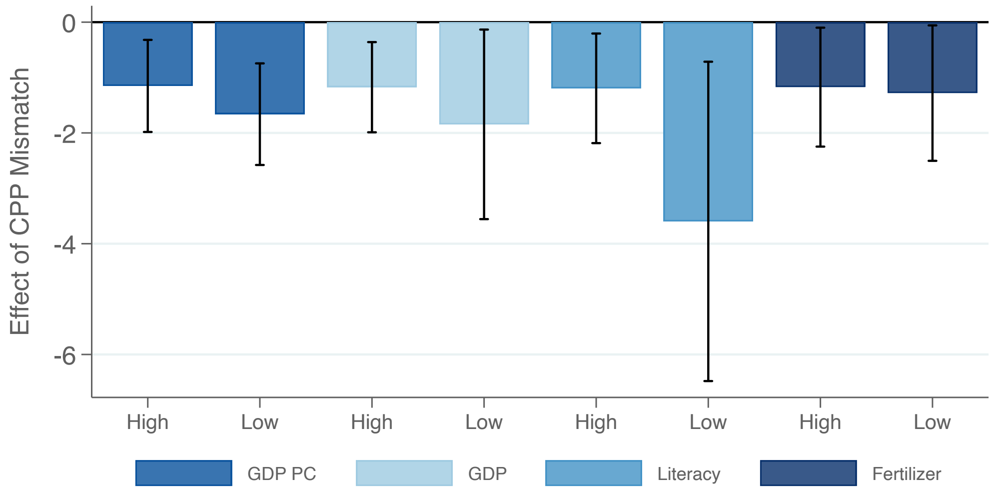
in modern agricultural research.[12] The second is to identify a set of crop-specific "leaders" $T_N(k)$ in the UPOV data, based on being among the top N countries in variety registrations for k. This data-driven approach sets $L_{k,\ell'} = \mathbb{I}[\ell' \in T_N(k)]$. In this specification, β^L captures the difference in the marginal effect of inappropriateness on technology diffusion when the origin country is a leader in biotechnology development.

We find that the negative effect of mismatch with the leader is consistently an order of magnitude larger than the effect of mismatch with other markets. Table 4 presents our results with the extensive margin of crop variety transfer as the outcome and for several definitions of the technology leader for each crop. For example, when we define the leader using the top 2 or 3 variety developers (columns 3 and 4 of Table 4), the marginal effect of CPP mismatch on technology diffusion is roughly twenty times larger for technology leader origin markets. The story is very similar focusing on the intensive margin of variety transfer (Table A4) and measuring technology transfer in the patent data, using either patent transfers or patent citations (Table A5).

Mismatch Has a Larger Effect for Innovation-Intensive Crops. We next test whether mismatch has a larger effect on diffusion for more innovation-intensive crops, in parallel to the earlier test for innovation-intensive origins. We define these crops using three strategies: identifying global staple crops (corn, wheat, soybeans, and rice), identifying the crops that receive the most varieties in our data, and identifying the crops for which genetically modified crops have been ever released.

[12]The US produces 30% of citation-weighted global agricultural science publications and three times as many patents as the next highest country (Japan). 52% of agricultural research and development companies are incorporated in North America and US inventors generate roughly 1.5 thousand patents for plant modification and 1 thousand patents for cultivar development per year (Fuglie, 2016).

Figure 4: Heterogeneous Effects of CPP Mismatch on Variety Transfer



Notes: All sets of bars report coefficient estimates from single regression estimates, versions of Equation 9 that interact crop pest and pathogen (CPP) mismatch with indicators that equal one if the country is above or below the global median for a series of country-level characteristics. The outcome variable is log of variety transfer. The characteristics are GDP per capita (2010 USD per person), total GDP (2010 USD), literacy among adults (percentage among people over 15 years old), and fertilizer use (kg per hectare of arable land), all measured from the World Bank in a global cross-section from 2000. Standard errors are double-clustered by origin and destination, and 95% confidence intervals are reported.

We estimate regression models that parallel Equation 10, but interacting CPP Mismatch with these crop-level characteristics. We find that the negative effect of CPP mismatch on technology transfer is strongest for innovation-intensive crops measured in all three ways (Table A6).

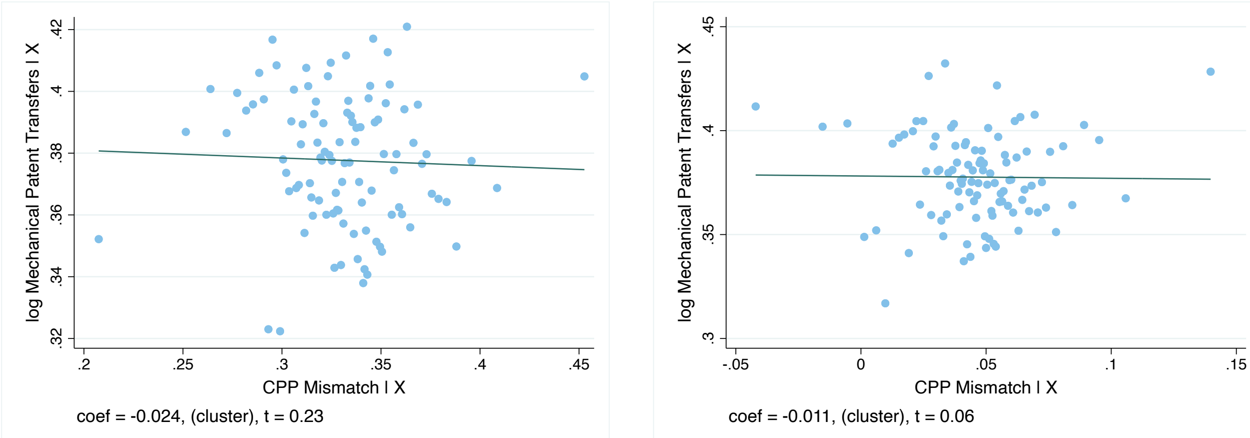
Mismatch Matters Even for Poor, Input-Scarce Destinations. In principle, other barriers to technology adoption could mediate the effects of mismatch on technology diffusion. In fact, a range of studies argue that the main if not only obstacle to modern technology use in low-income countries are wedges or deliberately constructed barriers to technology access (e.g., Parente and Prescott, 2002). These barriers would not bias our estimates of Equation 9, but might imply that the effect size is different for different markets. Our specific model in Section 2 advanced a stronger claim that any such local barriers to technology diffusion, which may certainly exist, have zero impact on the elasticity of technology transfer to mismatch. In particular, our model predicts that technology transfer is equally elastic to mismatch even in locations where wedges or constructed barriers to technology may be highest.

To study this, we test for heterogeneity of our main coefficient on the basis of several proxies for national and agricultural development. Figure 4 reports the effect of CPP mismatch separately for countries that are above versus below median per-capita GDP, total GDP, literacy, and fertilizer use (a common proxy of agricultural technology penetration; see e.g., Duflo et al. (2011)). Across the board, we estimate similar effects for both groups of countries. If anything, the coefficient estimate is always slightly *larger* for "less developed" markets — all point estimates imply an economically

Figure 5: Effect of CPP Mismatch on Transfer: Mechanical Technologies

(a) Mechanical Technology (Average Effect)

(b) Mechanical Technology (Leader Effect)



Notes: Each sub-figure reports a binned partial correlation plot in which all possible two-way fixed effects are absorbed. The outcome is log of the total number of mechanical patent transfers. Panel (a) reports the average effect of CPP mismatch (β in Equation 9) and panel (b) reports the effect of CPP mismatch with the leader (β^L in Equation 10).

large and statistically significant negative effect of mismatch on variety transfer even in relatively poor and input-scarce countries. This set of estimates further shows that the effect of CPP mismatch is driven by innovation decisions in leader countries and is *not* strongly mediated by proxies for potential technology demand in technology adopting countries.

5.4 Ruling Out Alternative Explanations

A Placebo Test with Mechanical Technologies. If estimates of Equation 9 capture the causal effect of CPP mismatch, we would expect a weaker effect when focusing on types of technology that cannot be meaningfully adapted to specific environments. A primary example is the class of mechanical technologies including harvesters and mowers: while these may have complementarities with biological technologies that *are* designed for particular environments, there are few ways to directly adopt these machines to local ecology. In the language of the model (Section 2), these technologies may feature high α, and therefore we predict a small (if any) effect of mismatch on their transfer (Proposition 1). On the other hand, confounding stories like a spurious correlation between environmental mismatch and expected future productivity might equally apply to mechanical and biological technologies. Therefore, to test our interpretation, we re-estimate our empirical models with the diffusion of mechanical technologies, as measured in the patent data, as the outcome.[13]

We find that CPP mismatch has limited effects, if any, on the transfer of mechanical technologies (Figure 5a). The effect is very close to zero even when focusing on CPP mismatch with the technological leader (Figure 5b). For comparison, Figures A2a and A2b report the same specifications as

[13]We identify mechanical patents as those that are assigned Cooperative Patent Classification (CPC) classes A01B, A01C, or A01D. This follows prior work on agricultural technology, including Moscona and Sastry (2023). For detailed CPC class definitions, see here: https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html.

Figure 5, but instead focus on biological and chemical technologies—the effect is large, negative, and significant. This heterogeneity across types of technology is consistent with our interpretation of the main results, but would *not* be expected under a story of spurious correlation with un-modeled characteristics.

Human Activity and Reverse Causality. A different threat to our interpretation is a form of reverse causality, to the extent that human activity affects the distribution of CPPs and hence our measure of CPP mismatch. However, we find no evidence that this is the case. First, we fully purge our measure of CPP mismatch by any variation due to eradications or invasive species, the two ways that human activity could affect CPP presence (or lack thereof) across markets. Our results are quantitatively almost identical when we remove variation due to eradications or due to species that have ever been invasive or have high invasive potential anywhere in the world (Table A7, columns 2-3; column 1 reports our baseline estimate for reference). Second, we find a large, negative effect of agro-climatic mismatch on variety transfer (Table A8). This mismatch measure is based on characteristics of temperature, precipitation, and topography that we might reasonably treat as predetermined over our studied sample. In Appendix C, we elaborate more on our measurement approach, the independent effects of different components of agro-climatic mismatch, and the interpretation of this second channel through which environmental differences affect technology transfer.

Other Omitted Variables. In principle, omitted variables at the *country-pair-by-crop* level could drive a spurious correlation between ecological mismatch and variety transfer. One candidate is trade. In column 4 of Table A7, we show that our main estimate is quantitatively similar if we control for an indicator that equals one if countries ℓ and ℓ' engage in bilateral final good trade for crop k. Another possibility is that the impact of distance (and hence economic ties) differs across crops in a way that is correlated with CPP mismatch. In column 5, we show that our results are unaffected by controlling for (log of) the geographic distance between all country pairs interacted with a full set of crop fixed effects. Finally, in columns 6 and 7 we entirely exclude from the sample any country pairs that are less than 1000 or 2000 kilometers apart, respectively. The estimate is again very similar, suggesting that the findings are not driven by geographically close countries. These findings suggest that the results are not driven by an omitted factor related to crop-specific links between country pairs.

5.5 Technology Transfer Without Intellectual Property

Before proceeding, we describe two additional analyses that show that the inappropriate technology hypothesis has bite in markets without intellectual property protection. Such markets are usually beyond the scope of empirical studies of innovation and technology transfer, but they are of especially great interest to studies of technology use and productivity differences in agriculture.

Variety Introduction in sub-Saharan Africa. We first study how mismatch with frontier technology producers affects variety introduction in sub-Saharan Africa, a region poorly covered by UPOV and by patent offices. We use data from the Consultative Group on International Agricultural Research (CGIAR) Diffusion and Impact of Improved Varieties in Africa (DIIVA) project, which, for 19 crops and 28 countries in sub-Saharan Africa, records all unique crop varieties made available since 1960. These data do not rely on information from intellectual property protection protection and were instead collected by hand. A glance at the data suggests that the reality of crop breeding in sub-Saharan Africa reflects a significant role for the public sector and a diminished role, if any, for familiar Western agro-chemical companies. For example, of the 214 novel maize varieties recorded in Kenya, 64 are associated with the Kenyan Agricultural Research Institute (KARI), a state-run research organization, and 45 with the Kenya Seed Corporation (KSC), a state-run corporation that markets improved varieties; Monsanto and Pioneer Hi Bred contribute 9 and 8, respectively.

Unlike our international variety registration or patent data, the DIIVA data do not systematically record the origin country for each variety. Nonetheless, we can test how mismatch affects the overall availability of improved technology. We find that country-crop combinations more mismatched with the frontier have fewer overall variety introductions, conditional on crop and country fixed effects (Figure A3). This is consistent with the hypothesis that ecological differences inhibit both the direct availability of foreign technology and the scientific and technological base for follow-on innovation (e.g., even by state-supported breeders). Our findings in the DIIVA data suggest that both mechanisms, which we previously measured through variety introductions, patents, and patent citations, also have an effect in setting without IP protection.

The Diffusion of the Green Revolution. We next study how environmental mismatch mediated the effects of the Green Revolution, a period of major investment in agricultural technology development that was coordinated by research centers in a few specific tropical countries and targeted toward parts of the world with under-developed agricultural technology markets. Questions about the reach and efficacy of the Green Revolution are central to many debates about 20th century agricultural development (Moseman, 1970; Ruttan and Hayami, 1973; Pingali, 2012). We use our data on crop-by-country-pair CPP mismatch to construct a measure of CPP mismatch with the crop-specific centers of breeding during the Green Revolution (see Section 6.5 for greater detail). We link these measures with data on the adoption of improved Green Revolution crop varieties across country-crop pairs, compiled by Evenson and Gollin (2003a). We find that CPP mismatch with the crop-specific locations of Green Revolution breeding (e.g., the CIMMYT in Mexico for corn or the IRRI in the Philippines for rice) significantly reduced the extent of adoption of high-yield varieties in the 1960s and 1970s (Figure A4). These results demonstrate the applicability of our findings to an earlier era of agricultural technology development and to innovations championed by non-profit-seeking actors in the public and philanthropic sectors.

6. Mismatch and Agricultural Production

We now study how mismatch with R&D leaders affects agricultural production. We find that mismatch with leaders substantially reduces output at the country-by-crop level: that is, countries specialize in the crops for which global technology happens to be most environmentally appropriate. Exploiting finer-grained variation that sweeps out country-level differences, we find quantitatively similar effects in a sub-national analysis of Brazil and India. We finally exploit two events, the Green Revolution and the recent rise of US biotechnology, that isolate *dynamic* variation in inappropriateness. Using these strategies, we show that the changing geography of agricultural innovation realigns global agricultural production by differentially affecting environments for which the new technology is more or less appropriate.

6.1 Empirical Strategy

Our estimating equation at the level of crops k and countries ℓ is derived in Proposition 2:

$$\log \text{Production}_{k,\ell} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell} + \chi_\ell + \chi_k + \Omega'_{k,\ell}\Gamma + \varepsilon_{k,\ell} \tag{11}$$

The outcome is (log) average production from 2000 to 2018 and $\Omega_{k,\ell}$ is a vector of potential controls. All specifications include country and crop fixed effects (χ_ℓ, χ_k).

$\text{CPPMismatchFrontier}_{k,\ell}$ measures the extent to which technology developed by R&D leaders is environmentally inappropriate for growing crop k in country ℓ. Motivated by our earlier empirical findings (Section 5.2), we define the technological frontier for each crop based on the frequency of variety releases in the UPOV data. Given a set $T_N(k)$ of the N top countries for k-variety releases, we calculate:

$$\text{CPPMismatchFrontier}_{k,\ell} = \sum_{\ell' \in T_N(k)} \left(\text{Share Varieties}^{\text{UPOV}}_{k,\ell'}\right) \times \left(\text{CPP Mismatch}_{k,\ell',\ell}\right) \tag{12}$$

where $\text{Share Varieties}_{k,\ell'}$ is calculated among the set $T_N(K)$ (i.e., these weights add to one). For our baseline results, we use $N = 2$; however, the results are very similar for alternative values for N.[14] As a secondary strategy that does not rely on additional data inputs, we assume that the United States is the leader for all crops: $\text{CPPMismatchFrontier}_{k,\ell} = \text{CPPMismatch}_{k,\text{US},\ell}$. While this method ignores many details about the geography of agricultural innovation, our results in Section 4 and 5 suggest that it is a reasonable approximation.

The model in Section 2 provides a precise interpretation for our estimating equation. The crop fixed effect χ_k absorbs global crop prices and the general-purpose component of crop-specific technology. The location fixed effect χ_ℓ absorbs the productivity of *other* crops in a given location as well as components of productivity or additional factors of production (e.g., human capital) that are common to a location. The composite term $\Omega'_{k,\ell}\Gamma + \varepsilon_{k,\ell}$ corresponds to the variable $\omega_{k,\ell}$ in the model, which summarizes other crop-by-location specific determinants of productivity. These may include geographic suitability or the extent of other *crop-specific* agricultural inputs. We will treat $\Omega'_{k,\ell}\Gamma$ as a component that can be spanned by observable controls and $\varepsilon_{k,\ell}$ as an unobservable component.

Our hypothesis is that $\beta < 0$, or that countries produce less of crops for which their local environment differs from that of technological leaders. In spite of our earlier findings that mismatch inhibits technology transfer (Section 5), we might nonetheless find $\beta = 0$ if the availability of new

[14] The full set of crop-specific technology leaders for $N = 2$, as well as the number of crops for which each country is identified as a leader, is presented in Table A9.

agricultural varieties or presence of patented technologies does not translate into substantially more technology use by farmers, or if shifting technology use independently from other economy-wide characteristics has little effect on output.

Identification. The parameter β is identified via ordinary least squares if CPP mismatch with the frontier is uncorrelated with the unobservable component of productivity in $\varepsilon_{k,\ell}$, conditional on fixed effects. We first argue that this is *ex ante* plausible: that is, environments that are similar to those of R&D leaders are not inherently "good," when one ignores the effects of (endogenously appropriate) technology. Early efforts to develop technology for agricultural expansion in the United States were stymied by an unfamiliar and hostile pest and pathogen environment (Olmstead and Rhode, 2008). Much of this effort focused on the "Great American Desert," which was then "considered incapable of supporting agriculture" (Olmstead and Rhode, 2011, p. 482)—and is now known as the Great Plains, producing much of the world's wheat, corn, and soybeans. Contemporary empirical studies also suggest that variation in local land suitability plays a limited role in explaining global productivity differences (Adamopoulos and Restuccia, 2022). This suggests that ecological similarity to today's technology leaders may not correlate with having *ex ante* favorable environmental conditions.

Nevertheless, to make this point empirically, we propose several approaches for accounting for the effect of *ex ante* differences in local characteristics. As a first strategy, we control for potential output in the FAO Global Agro-Ecological Zones (GAEZ) agronomic model. As a second, more data-intensive strategy, we compile a larger set of covariates and then use post-double LASSO (see Belloni et al., 2014) to discipline their selection. These include fixed effects for the 200 most geographically prevalent CPPs in our data (i.e., those that appear in the most countries) and the 200 most agriculturally prevalent (i.e., those that affect the most crops) and ten measures of agro-climatic conditions that describe temperature, precipitation, soil characteristics, and topography (see Appendix C), interacted with crop fixed effects to allow for crop-specific effects. Third, to gauge whether our regressor simply picks up ecologically "strange" places that are dissimilar from any other location, we conduct a placebo test that randomizes the identity of R&D leaders.

We finally use two additional empirical strategies that exploit additional variation across (finer-grained) space and time. We first study the effects of mismatch *sub-nationally* within Brazil and India, allowing us to sweep out country-by-crop level variables like trade or food policy (Section 6.4). We also study two dynamic natural experiments, the Green Revolution and the rise of US biotechnology, which allow us to completely absorb any static observables or unobservables, as well as trends in *ex ante* local productivity (Section 6.5).

6.2 Inappropriateness Reduces Agricultural Output

Our main estimates of Equation 11 are reported in Table 5. We find that countries have lower agricultural output for crops for which their environment is mismatched with technological leaders. Our baseline estimate with no additional controls (column 1) implies that a one standard deviation increase in CPP mismatch lowers output by 0.42 standard deviations. The negative effect of CPP mismatch on crop-specific output is robust to controls for FAO-GAEZ predicted output (column 2),

Table 5: CPP Mismatch Reduces Agricultural Output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Mismatch with Estimated Frontier				CPP Mismatch with the US			
CPP Mismatch (0-1)	-7.136	-5.721	-7.202	-6.288	-9.285	-10.600	-9.325	-8.454
	(0.959)	(0.663)	(0.461)	(0.501)	(1.199)	(3.024)	(0.617)	(0.652)
log(FAO-GAEZ-Predicted Output)		0.353				0.298		
		(0.0499)				(0.0814)		
Included in LASSO Pool:								
Top CPP Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Ecological Features x Crop Fixed Effects	-	-	No	Yes	-	-	No	Yes
Controls in LASSO Pool			335	3935	-	-	335	3935
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,704	2,353	6,707	5,903	6,926	2,353	6,931	6,069
R-squared	0.600	0.609			0.599	0.617		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP mismatch with the estimated set of technological leader countries and columns 5-8 use CPP mismatch with the US. Columns 1-2 and 5-6 report OLS estimates and columns 3-4 and 7-8 report post double LASSO estimates. Country and crop fixed effects are included in all specifications, and included in the amelioration set in the post-double LASSO specifications. The Top CPPs are defined as the top 200 CPPs defined by (i) the number of countries in which they are present and (ii) the number of host crops that they infect. Since the two sets overlap, the total number is 335. The set of ecological features includes: temperature, precipitation, elevation, ruggedness, growing season days, soil acidity, soil clay content, soil silt content, soil coarse fragment volume, and soil water capacity. Standard errors are double-clustered by crop and country.

and controls for a wide array of CPP environment and agro-climatic conditions selected by LASSO (columns 3 and 4). Thus, the baseline estimate does not seem to be driven by differences in the direct effect of local ecological conditions or *ex ante* suitability. The results are also all similar if we define the US as the technological leader country for all crops (columns 5-8).[15] Consistent with the prediction of the model, we find quantitatively very similar effects focusing on area as the outcome instead of production (Table A10).

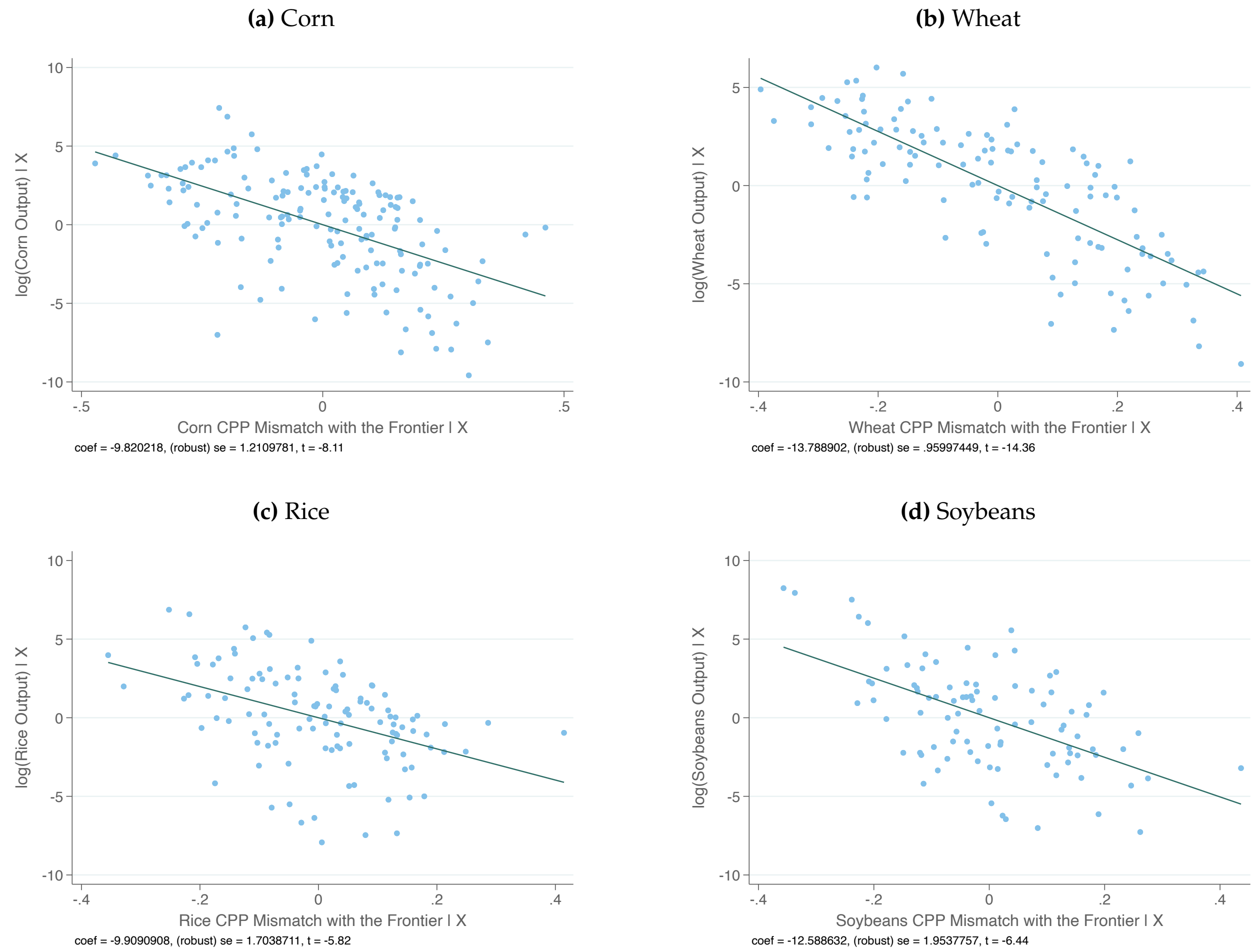
Figure 6 displays the negative cross-country relationship between CPP mismatch and output for four large crops: corn, wheat, rice, and soybeans. These findings convey the stark implications of our results for the world's most cultivated staple crops. The scatter plots also convey that the findings do not seem driven by any outliers or extreme parts of the distribution. There is a systematic, negative relationship between CPP mismatch and output across countries.[16]

Sensitivity and Robustness. We conduct a range of sensitivity checks that are analogous to those from the previous section, so we only mention them briefly here. First, we show that our results are

[15]One benefit of this specification is that the country fixed effects in (11) become tantamount to country *pair* fixed effects and therefore fully absorb all features of each country's relationship with the US.

[16]Since the single-crop results do not include country fixed effects, an additional prediction is that there should be a negative relationship between CPP mismatch with the frontier and output per area (i.e., crop yields). In Figure A5, we present an analogous set of partial correlation plots with yield as the dependent variable, and estimate negative and significant coefficients in for all crops. For comparison, we also include partial correlation plots with log of yield as the dependent variable for the full sample of crops, both with and without country fixed effects.

Figure 6: CPP Mismatch and Agricultural Output: Large Crops

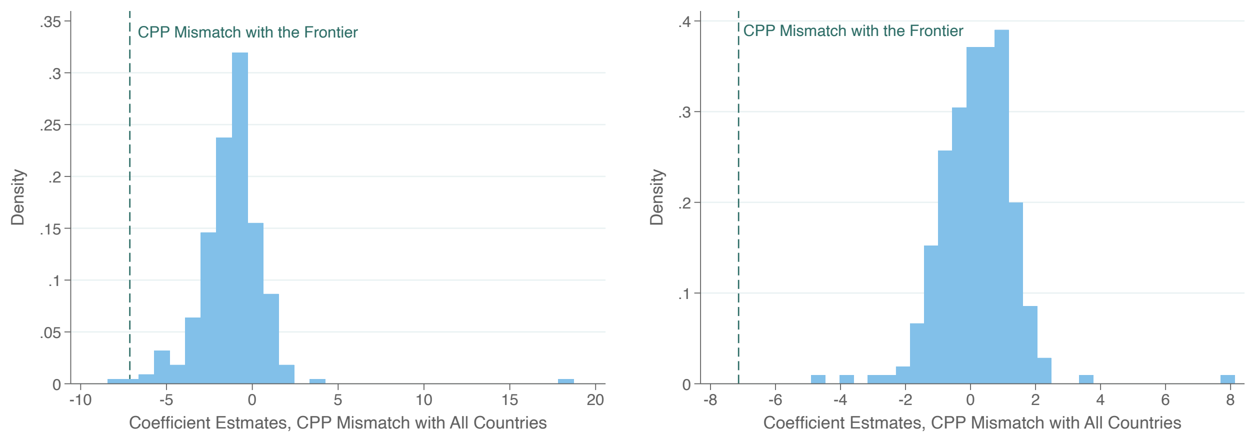


Notes: Each sub-figure reports a partial correlation plot of an estimate of (11) in which we restrict the sample to a single crop: corn, wheat, rice, and soybeans in 6a - 6d respectively. CPP mismatch is measured using the version in which we allow technological leadership to vary across crops. The coefficient estimates and standard errors are noted at the bottom of each sub-figure.

very similar if we purge any variation in CPP mismatch that could be driven by human activity, by re-incorporating all eradicated CPPs and removing all invasive or potential invasive CPPs (Figures A6a and A6b). Second, we show qualitatively very similar results using agro-climatic mismatch, a fixed shifter of ecological mismatch that is not subject to human manipulation (Figure A6c and Appendix Section C for additional detail). Third, we show that the results are quantitatively very similar if we absorb continent-by-crop fixed effects, thus only focusing on comparisons across crops and between countries *on the same continent* (Table A11). Fourth, in Table A12, we show that the results are also robust to controlling for the interaction of crop fixed effects with additional country-level characteristics (income, openness to trade, measures of inequality, specialization in agriculture, overall agricultural productivity, and R&D investment). Thus, our finding does not seem to be biased by spurious correlation between ecological mismatch and other determinants of productivity, even

Figure 7: Falsification Test: CPP Mismatch with All Countries and Output (2000s)

(a) Unconditional **(b)** Conditional on CPP Mismatch with the Frontier



Notes: This figure displays histograms of the coefficient estimates of the relationship between CPP mismatch with each country separately and the log of crop-level output. In 7a, CPP mismatch with each country is included on the right hand side of the regression alone (along with crop and country fixed effects) and 7b, CPP mismatch with the frontier is also included in the regression.

when these determinants of productivity are allowed to vary by crop.

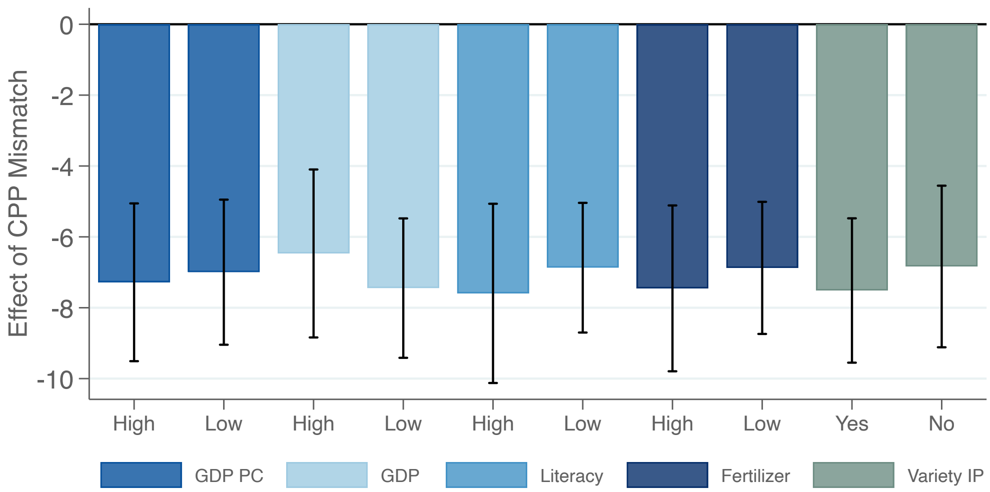
Finally, we account directly for the possibility that innovation could respond to potential future market size and that, if spuriously correlated with CPP mismatch, this could bias our estimates. Following Bustos et al. (2016), we construct a variable that measures the potential market expansion from improved varieties by taking the the difference between (log of) FAO-GAEZ predicted potential output under high input levels and (log of) FAO-GAEZ predicted potential output under low input levels. Our estimates are quantitatively unaffected by controlling for this variable (Figure A7).

6.3 Testing the Inappropriate Technology Mechanism (Redux)

Mirroring our analysis in Section 5.3, we now test additional predictions of our hypothesis: that mismatch matters more when it is relative to technological leaders and for innovation-intensive crops, and that the effects hold at various levels of income, physical capital, and human capital.

Mismatch with the Frontier Matters Most (Falsification Test). If our main estimates capture the effect of directed innovation on agricultural productivity, then we would expect to find a limited effect of CPP mismatch with countries that are *not* centers of biotechnology development. To test this, we re-estimate Equation 11, replacing $\text{CPPMismatchFrontier}_{k,\ell}$ with CPP mismatch with each country in the world. Figure 7 reports histograms of these coefficient estimates, both from specifications that do not include CPP mismatch with the frontier as a control (7a) as well as from specifications that do (7b). In both cases, the coefficient on CPP mismatch with the frontier, marked with a dotted line, is in the left tail of the coefficient distribution.These estimates are consistent with a causal effect of inappropriate technology underlying our main estimates, and help rule out the

Figure 8: Heterogeneous Effects of CPP Mismatch on Output



Notes: All sets of bars report coefficient estimates from single regression estimates, versions of Equation 11 that interact CPP mismatch with indicators that equal one if the country is above or below the global median for a series of country-level characteristics, or whether or not the country has IP protection for plant varieties (i.e., is UPOV compliant). The outcome variable is log of production. The characteristics are GDP per capita (2010 USD per person), total GDP (2010 USD), literacy among adults (percentage among people over 15 years old), and fertilizer use (kg per hectare of arable land), all measured from the World Bank in a global cross-section from 2000. Standard errors are double-clustered by crop and country, and 95% confidence intervals are reported.

possibility that omitted ecological characteristics (e.g., ecological uniqueness) bias our results.

Mismatch Has a Larger Effect for Innovation-Intensive Crops. We next study heterogeneity in the effect of mismatch on agricultural production by the innovation intensity of different crops by estimating versions of Equation 11 that interact CPP Mismatch with crop-level variables. The effects of CPP mismatch on output are larger for staple crops, the crops with the most global variety releases, and the crops for which a genetically modified variety was brought to market (Table A13). These are the same crops for which we earlier found an exaggerated effect of CPP mismatch on technology transfer (Table A6).

Mismatch Matters Even for Poor, Input-Scarce Destinations. An additional prediction of our model, borne out also in our results on technology transfer (Figure 4), is that the inappropriate technology hypothesis has bite even in low-income and input-scarce destinations. We find similar results when studying the heterogeneous effects on production, as summarized in the first four pairs of bars in Figure 8. That is, inappropriateness reduces crop-specific output even in countries with low income, low human capital, and low agricultural input use.

Mismatch Matters With and Without IP Enforcement. An additional test that was not possible in our analysis of variety transfers was whether mismatch has differential effects in parts of the world with and without intellectual property protection for plant varieties. The last panel of Figure 8 suggests that CPP mismatch has negative and significant effects in both cases. This is consistent of our findings that CPP mismatch inhibits technology diffusion even in markets with limited or absent IP enforcement (Section 5.5). The similar effect on the sample without IP enforcement, moreover, makes it unlikely that the main result is driven by a spurious correlation between innovators' anticipated future demand for their products and CPP mismatch since inventor profit margins in regions without IP enforcement would likely be low everywhere. Moreover, this finding further highlights the fact that the potential impact of technology mismatch on production in a given country is independent from characteristics of local output or input markets.

6.4 Inappropriateness Reduces Agricultural Output Within Countries

We can exploit state-level data for Brazil and India to estimate the effects of mismatch at a sub-national level. Our estimating equation is:

$$y_{k,s} = \beta \cdot \text{CPPMismatchFrontier}_{k,s} + \chi_s + \chi_{k,\ell(s)} + \Omega'_{k,s}\Gamma + \varepsilon_{k,s} \tag{13}$$

where now s indexes states and $\ell(s) \in \{\text{Brazil}, \text{India}\}$. In all specifications, we include crop-by-country fixed effects ($\chi_{k.\ell(s)}$). By estimating the effect of inappropriateness on sub-national regions, we hold fixed all country-by-crop characteristics, including crop-specific R&D, trade, policy, market size, demand, and pest composition. Absorbing these determinants of productivity further sharpens our identification strategy. Compared to our main results, estimates of Equation 13 exploit finer differences in ecological conditions, making comparisons within both crops and states, and home in on *ex ante* similar markets that nevertheless differ in their environmental similarity to technology leaders (e.g., corn vs. cotton in Mato Grosso or soy in Mato Grosso vs. soy in Rio Grande do Sul).

We find negative and significant estimates of β (Table 6). The estimates are stable to different control strategies, similar for the data-driven leader strategy and the US-as-leader strategy, and comparable in magnitude to our country-by-crop results up to statistical precision. These findings suggest that unobserved differences across country-crop pairs do not drive our findings. Moreover, they imply that technology mismatch explains productivity differences not only across international markets but also differences across regional markets within countries, which represent a growing share of global inequality. This is consistent with existing conjectures that variation in technology use can explain a large share of sub-national productivity differences (Acemoglu and Dell, 2010).

6.5 Dynamic Estimates: The Green Revolution and Rise of the US

So far we have studied the static effect of inappropriateness on production. We now investigate how changes in technological leadership over time influence production, by shifting global patterns of inappropriateness. To study this topic, we exploit two natural experiments that significantly shifted the geography of agricultural innovation: the Green Revolution of the 1960s and 1970s and the rise of US biotechnology since the 1990s. Methodologically, these strategies allow us to fully absorb any unobservable crop-by-country level effects when estimating the dynamic impact of CPP mismatch on production. Conceptually, these results highlight that the impact of local ecology on productivity is not fixed but an outcome of the shifting direction of innovation.

Table 6: CPP Mismatch Reduces Agricultural Output: Within-Country Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Mismatch with the Estimated Frontier				CPP Mismatch with the US			
CPP Mismatch (0-1)	-11.890	-10.100	11.850	-10.370	-8.925	-10.200	-8.695	-9.355
	(1.937)	(2.475)	(1.538)	(2.247)	(2.386)	(3.327)	(1.752)	(2.096)
log(FAO-GAEZ-Predicted Output)		0.659				0.654		
		(0.133)				(0.138)		
Included in LASSO Pool:								
Top CPP Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Ecological Features x Crop Fixed Effects	-	-	No	Yes	-	-	No	Yes
Crop x Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,370	696	1,371	1,036	1,436	696	1,437	1,093
R-squared	0.658	0.683			0.641	0.680		

Notes: The unit of observation is a state-country pair. Columns 1-4 use CPP mismatch with the estimated set of technological leader countries and columns 5-8 use CPP mismatch with the US. Columns 1-2 and 5-6 report OLS estimates and columns 3-4 and 7-8 report post double LASSO estimates. State and crop-by-country fixed effects are included in all specifications, and included in the amelioration set in the post-double LASSO specifications. The Top CPPs are defined as the top 200 CPPs defined by (i) the number of countries in which they are present and (ii) the number of host crops that they infect. Since the two sets overlap, the total number is 335. The set of ecological features includes: temperature, precipitation, elevation, ruggedness, growing season days, soil acidity, soil clay content, soil silt content, soil coarse fragment volume, and soil water capacity. Standard errors are double-clustered by crop and state.

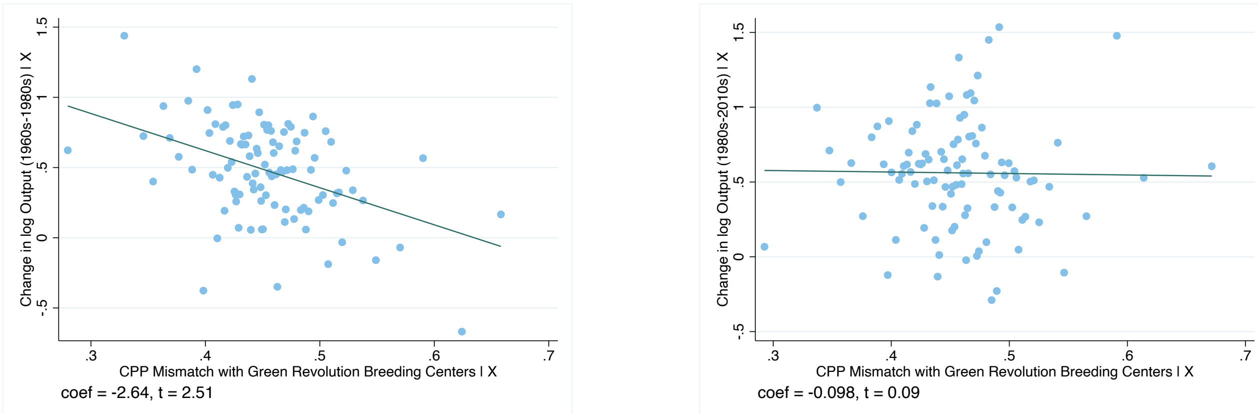
The Green Revolution. The Green Revolution was a coordinated international effort, backed by philanthropic organizations, to develop high-yielding varieties (HYVs) of staple crops for countries with high risk of famine. The engine at the heart of the Green Revolution was a set of international agricultural research centers (IARCs), including the International Rice Research Institute (IRRI) in the Philippines and the International Maize and Wheat Improvement Center (CIMMYT) in Mexico. We identify from Evenson and Gollin (2003b) the IARC and hence country in which the primary breeding center for each crop was located (Table A14). While HYV breeding involved international collaboration, the focus of activity in certain hubs anecdotally led to technology most appropriate for primary breeding locations.

We exploit the shift of innovation toward the IARCs to identify how changes in the focus of innovation affect global production. To measure the induced changes in crop-by-country inappropriateness, we compute CPP mismatch with centers of Green Revolution breeding at the crop-by-country level as $\text{CPPMismatchGR}_{k,\ell} = \text{CPP Mismatch}_{k,\ell,\ell^{GR}(k)}$, where $\ell^{GR}(k)$ is the index of the country in which Green Revolution breeding of crop k was located. In Section 5.5, we showed that this measure of mismatch with Green Revolution breeding strongly predicts the extent of adoption of high-yield varieties as measured by Evenson and Gollin (2003a,b), validating it as a shifter of the appropriateness Green Revolution technology.

Our measure of mismatch suggests that potential appropriateness of Green Revolution technologies varies substantially across places and crops. In Figure A8, we illustrate the variation in CPPMismatchGR for three examples: wheat at the CIMMYT in Mexico, rice at the IRRI in the

Figure 9: Inappropriateness and the Impact of the Green Revolution

(a) Green Revolution Period (1960s-1980s) **(b)** After the Green Revolution (1980s-2010s)



Notes: This figure displays binned partial correlation plots, after absorbing country and crop-by-continent fixed effects, in which the independent variable is $\text{CPPMismatchGR}_{k,\ell}$ and the dependent variable is the log of agricultural output. In (a), the outcome is differenced over the 1960s-1980s and in (b), it is differenced over the 1980s-2010s. Standard errors are clustered by country and continent-crop.

Philippines, and sorghum at ICRISAT in India. We also show the *difference* between mismatch with these centers and mismatch with the United States, a simple proxy for the technological frontier. In all cases, Green Revolution technology is systematically more appropriate for tropical biomes than US technology. But this masks substantial heterogeneity within and across crops. For example, our measure suggests that the environment in which ICRISAT researched sorghum varieties in India was more similar to much of sub-Saharan Africa than the environment in which the CIMMYT research wheat varieties in Mexico.

We estimate how CPP mismatch with Green Revolution centers affected output growth from the 1960s to the 1980s via the following regression model:

$$\Delta \log y_{k,\ell}^{80-60} = \beta \cdot \text{CPPMismatchGR}_{k,\ell} + \tau \cdot \log y_{k,\ell,1960s} + \chi_\ell + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \tag{14}$$

where the dependent variable is the *change* in (log of) crop-level output between the 1960s and the 1980s, and the sample includes all crop-country pairs from the HYV adoption model. This estimating equation differences out a country-by-crop fixed effect in *levels* of production, or the time-invariant effects of local suitability. To even more strongly account for differences in innate productivity, we control directly for output in the 1960s ($\log y_{k,\ell,1960s}$), which captures differential trends in initial output.

We estimate $\beta < 0$ between the 1960s and the 1980s: all else equal, production grew less in environments for which Green Revolution technology was less appropriate (Figure 9a). We find no effect of Green Revolution Mismatch after the new adoption of Green Revolution technology began to decline after the 1980s (Figure 9b), indicating that our main result is not spuriously capturing long-run trends in productivity across country-crop pairs.

Our findings are consistent with existing case-study evidence about how pest dissimilarities shaped the efficacy of Green-Revolution technology (e.g., Lansing, 2009). The finding also illustrates how the Green Revolution's focus on developing a small set of HYVs and distributing them widely may have limited the movement's global reach, since new varieties were less productive in, and less likely to be adopted in, environments ecologically different from HYV breeding centers.

The Rise of US Biotech. Since the 1990s, the US biotechnology sector has grown rapidly while the European biotechnology sector has, in relative terms, declined. Industry analysis observe that these trends coincide with the advent of genetic modification technology and the very different regulatory approach to this technology in the US versus Europe, spurring a large increase in private capital investment in the US (Fernandez-Cornejo and Caswell, 2006, p. 2). Figure A9 shows the footprint of these trends in our own patent data: while there were more agricultural patents in Europe than in the US during the 1990s, the US far outpaced Europe by the 2010s.

We exploit this disproportionate growth of the US as a second identification strategy to measure the effects of mismatch on production. For each country-crop pair, we estimate:

$$\Delta \log y_{k,\ell}^{10-90} = \beta_1 \cdot \text{CPP Mismatch}_{k,\ell}^{US} + \beta_2 \cdot \text{CPP Mismatch}_{k,\ell}^{EU} + \gamma \cdot \log y_{k,\ell}^{1990} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \quad (15)$$

Like our Green Revolution strategy, this specification allows us to fully absorb country and crop specific trends, as well as trends in baseline production ($\log y_{k,\ell}^{1990}$). We hypothesize that production has reallocated toward places ecologically similar to the US ($\beta_1 < 0$) and away from Europe ($\beta_2 > 0$) due to the underlying shift in the geography of innovation. We find evidence of both hypotheses (Table A15). The effect of the US, β_1, is negative and statistically significant in all specifications. The effect of the EU, β_2, is positive, although imprecisely estimated. When we conduct a permutation analysis and compare the impact of CPP mismatch with the US on output changes with the effect of CPP mismatch with all other countries on the globe, the effect of CPP mismatch with the US is in the far left tail of the distribution (see Figure A10; p-value = 0.004), consistent with the fact that the growth of US innovation was much more dramatic than that of any other country during this period. Additionally, the effect is substantially larger for major US field crops (corn, wheat, soybeans, and cotton), for which US seed market growth was "particularly rapid" during the sample period and ultimately constituted over two-thirds of US market size (Fernandez-Cornejo and Caswell, 2006) (see Panel B of Table A15). These results, taken together, are consistent with a causal interpretation that R&D growth and environmental mismatch affect global agricultural specialization.

7. Inappropriate Technology and Agricultural Productivity

We finally combine our empirical estimates with the model to study how the inappropriateness of technology shapes the distribution of global agricultural productivity. We then use our framework to study a series of counterfactual scenarios that model how inappropriateness affects the optimal targeting of new research, the consequences of a global shift in R&D toward emerging markets, and the global movement of crop pests and pathogens due to climate change.

7.1 Methods

Set-up. We make three modifications to the model of Section 2. First, the "Leader" producer of biotechnology may differ for each crop, to match the data and our empirical specification. We let L_k denote the leader for each crop k. Second, each country has endowment ζ_ℓ of agricultural land. Third, we explicitly specify a demand system. There is a representative global consumer with payoffs $u(M, C)$ defined over the numeraire good ("money") and a constant elasticity of substitution bundle of the agricultural goods:[17]

$$C = \left(\sum_{k=1}^{K} \kappa_k^{\frac{1}{\varepsilon}} C_k^{1-\frac{1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{16}$$

for some constants $(\kappa_k)_{k=1}^K$ and elasticity of substitution $\varepsilon > 0$.[18] The representative consumer can purchase each crop k at a global price p_k, in terms of the numeraire. The role of the demand system is to help us account for equilibrium responses of crop prices.footnoteWe furthermore assume that γ, landowners' profit share, is ≈ 1, so the elasticity of choices to prices is $\eta/\gamma \approx \eta$.

From Regression Estimates to Quantification. Revisiting Proposition 2 with these additional assumptions, we can write crop-by-country output as

$$\log Y_{k,\ell} = -\beta\, \delta_{k,L_k,\ell} + (\eta - 1) \log \hat{p}_k - (\eta - 1) \log \hat{\Xi}_\ell + \log \zeta_\ell + \eta \left(\alpha A_k + (1 - \alpha) \underline{B} \right) + \eta \log \omega_{k,\ell} \tag{17}$$

where δ_{k,ℓ,L_k} is CPP mismatch with the crop-specific frontier, $\log \hat{p}_k = \log p_k - \log p$ is the price deviation from the agricultural price index $\log p$, and $\log \hat{\Xi}_\ell = \log \Xi_\ell - \log p$ is location-specific productivity deflated by the same index.[19] Agricultural productivity, as derived in Proposition 3, is

$$\log \hat{\Xi}_\ell = \chi + \frac{1}{\eta} \log \left(\sum_{k=1}^{K} \hat{p}_k^{\eta} \omega_{k,\ell}^{\eta} C_\ell^{-\eta \frac{1-\gamma}{\gamma}} A_k^{\alpha\eta} e^{-\beta \delta_{k,L_k,\ell}} \right) \tag{18}$$

Before describing the calibration, we highlight the two key contributions of the model that make it possible to map our regression estimates to aggregate productivity effects.

The first concerns the interpretation of our empirically estimated semi-elasticity of production to CPP mismatch from Section 6. Inspecting Equation 18, we observe that a one-unit reduction in mismatch δ increases productivity by β/η units. This adjustment factor of $1/\eta$ translates our regression coefficient from units of "production" to units of "productivity," by dividing out the elasticity of farmers' choice to changes in productivity. When η is smaller, farmers' crop choice is less sensitive to productivity differences, so the same effect of mismatch on production implies a larger effect on productivity. Moreover, the functional form of Equation 18 incorporates curvature

[17] Formally, the consumer's payoffs are represented by some concave $u : \mathbb{R} \times \mathbb{R}_+ \to \mathbb{R}$. They have an initial endowment of M, and are allowed to consume negative amounts.

[18] We normalize the constants κ_k so that, in the observed equilibrium, $p_k \equiv 1$ for all k.

[19] Deflating by the price p is natural because it keeps constant the representative consumer's overall demand for agricultural products.

that would be ignored by simple linear extrapolation.

The second concerns equilibrium price effects. If all countries become more productive at producing a certain crop, then the equilibrium price goes down, muting farmers' incentives to plant that crop. The model allows us to recover this "missing intercept" of equilbrium interactions, which was controlled for in the crop fixed effect of the regression. The elasticity of demand ε controls the strength of this channel: if demand is more inelastic, then price effects are larger.

Calibration. We calibrate the Fréchet parameter as $\eta = 2.46$ from Costinot et al. (2016), who estimate this parameter to match the modern cross-section of global agricultural production. Combining this estimate with our baseline estimate of $\beta = -7.14$ (Table 5, column 1) yields an estimate of $-\beta/\eta = 2.90$, in units of percent productivity loss per basis point of CPP mismatch.

Conditional on η, the crop-by-location productivity $\omega_{k,\ell}$ is identified up to scale from data on relative area by crop. We measure these areas using the crop-by-country planting data from the FAOSTAT database, averaged from 2000-2018. We use estimates of total agricultural revenue from Fuglie (2012), again averaged from 2000 to the present, to calibrate all countries' initial revenue productivity and extent of agricultural land. This pins down the scale of local innate productivity. Finally, to calibrate the crop-level demand curves, we use the elasticity of supply between crops estimated by Costinot et al. (2016), $\varepsilon = 2.82$.

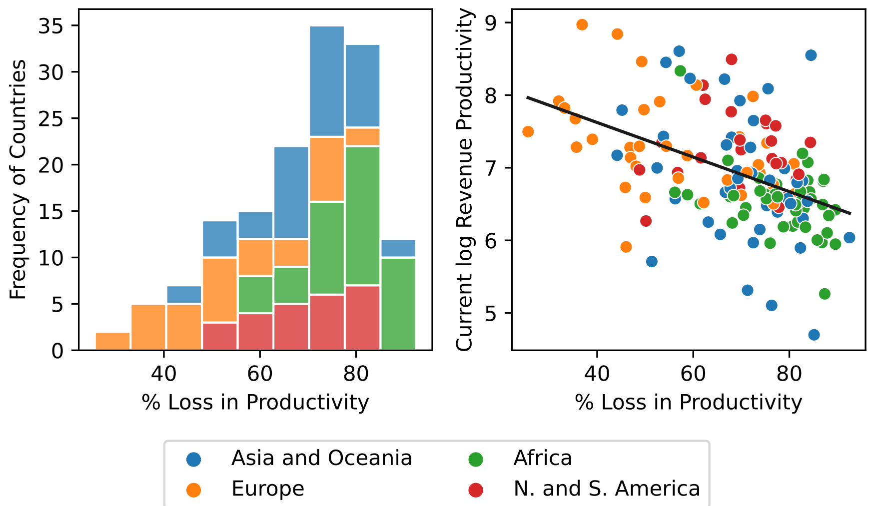
7.2 The Productivity Effects of Inappropriateness

We first study a counterfactual in which global agricultural innovation becomes evenly focused. In the language of the model, innovators invest in R&D for all ecological conditions and $B_{t,k,\ell} \equiv \bar{B}$. In the language of the Introduction's motivating example, frontier research related to the Maize Stalk Borer catches up to frontier research related to the "Billion Dollar Bug," the Corn Rootworm. Without taking a stand on the costs of research and the origins of unevenly focused innovation, we cannot make a normative claim that this scenario is preferred to the *status quo*. Nonetheless, it is a natural benchmark for gauging the extent to which inappropriate technology can account for the vast differences in global agricultural productivity.

Based on comparing the observed equilibrium with this counterfactual, we find that inappropriateness reduces global productivity by 57.7% (SE: 4.85%) and explains 15.1% (SE: 0.42%) of global disparities, as measured by the inter-quartile range of the log productivity distribution. The left panel of Figure 10 displays the distribution of productivity losses across continents. The largest losses from inappropriateness are concentrated in Africa and Asia, while the smallest are in Europe. The right panel plots observed log revenue productivity against the model's losses from inappropriateness. The negative correlation ($t = -6.22$) conveys that the countries with the highest predicted loss from inappropriateness are the least productive today. That is, neglected agricultural ecosystems are disproportionately located in unproductive parts of the world, which are kept unproductive due to an absence of appropriate technology.[20]

[20] Figure A11 summarizes sensitivity analysis of our main findings to alternative calibrations of η and ε. The findings are similar for the full range of plausible values that are consistent with estimates from the literature.

Figure 10: The Effects of Inappropriateness on Global Agricultural Productivity



Notes: This figure presents results from the counterfactual experiment of equalizing research on all ecological characteristics (see Section 7.2). We present results by calculating the loss in agricultural productivity moving from the counterfactual world of equalized research to the observed world of unequal research. The left graph is a histogram of productivity losses from inappropriateness across countries. The right graph is a scatterplot of productivity losses against observed productivity. The line is a best-fit linear regression across countries (slope = −0.024, robust SE = 0.004). In each plot, colors indicate continents.

Inappropriateness Due to Other Ecological Differences. As highlighted in Section 3.1.3, CPP mismatch is not the *only* determinant of inappropriateness; other features of ecological and geographic mismatch with the frontier could contribute to the inappropriateness of modern technology and aggregate effect of inappropriateness on global productivity. Incorporating these additional dimensions of mismatch increases our estimate of the losses due to inappropriateness to 68.2%, and increases the effect on disparities in productivity to 16.3% (see also Appendix C and Figure A12).

7.3 Targeting Research for Maximum Global Impact

In the face of persistent global hunger and looming threats including climate change, there are renewed calls for a "Second Green Revolution" that benefits a broader set of low-income countries (Gates, 2009). Our measurement strategy and model can be used to ask which locations for potential research investments would maximize potential productivity benefits. For each of the eight staple crops which were the focus of the historical Green Revolution, we calculate the counterfactual general-equilibrium productivity benefit of moving the "Leader" to each country in the world. We then identify which new Leader choices would have the largest effect on global productivity and on productivity in currently less productive countries.

Our findings, reported in Table 7, are consistent with the hypothesis that a lack of breeding in Africa holds back global productivity growth (Pingali, 2012), especially in currently unproductive locations. Nigeria, Ghana, Zimbabwe, Tanzania, and the Democratic Republic of Congo all emerge as countries where breeding research could potentially have large effects on global output. Our

Table 7: Inappropriateness-Minimizing Centers for Modern Agricultural Innovation

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sites Chosen to Minimize Global Inappropriateness				Sites Chosen to Minimize Inappropriateness in Countries with Below Median Productivity			
Crop	Best Site	% Change in Productivity	Second Best Site	% Change in Productivity	Best Site	% Change in Productivity	Second Best Site	% Change in Productivity
Wheat	China	4.87	India	2.75	India	11.17	Pakistan	6.76
Maize	China	13.40	USA	10.24	India	9.08	Tanzania	7.61
Sorghum	India	1.26	Nigeria	1.11	Nigeria	3.39	India	3.08
Millet	Nigeria	1.37	India	1.04	Nigeria	3.43	Zimbabwe	2.02
Beans	India	1.99	Brazil	1.73	India	3.93	China	1.82
Potatoes	China	1.48	India	0.73	India	1.20	China	0.65
Cassava	Nigeria	0.64	Ghana	0.47	Nigeria	1.81	DRC	1.45
Rice	China	10.74	India	9.59	India	16.65	Thailand	10.98

Notes: Column 1 reports the crops included in our analysis of the Green Revolution. Columns 2-5 report the results of our analysis to select the two countries where breeding investment would have the largest positive effect on global output for each crop. Columns 6-9 report the results of our analysis to select the two countries where breeding investment would have the largest positive effect on output in countries with below median overall agricultural productivity. All estimates rely on the full model with non-linear adjustments and price responses.

results also suggest potentially large opportunities for emerging economies, like India and China. In the next section, we directly explore the rise of large, emerging markets and how their growing role in global R&D could shape global productivity.

7.4 The Rise of New Technology Leaders

One of the biggest changes to global R&D in the coming decades could be the rise of large emerging economies such as the "BRIC" countries—Brazil, Russia, India, and China. Our data reveal that agricultural patenting in BRIC countries, while still substantially behind that of the US, has grown at a faster rate since 1990s. This trend will likely accelerate in the future.

How might this shift in the geography of global research affect global agricultural productivity? To study this in our model, we set mismatch with the leader equal to a (area-weighted average) of mismatch with the BRIC countries:[21]

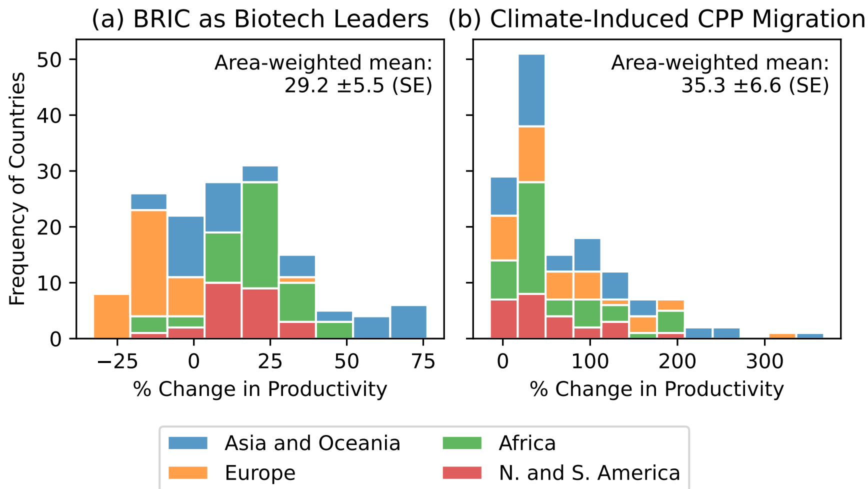
$$\delta_{k,\ell,L_k} = \sum_{\ell' \in \text{BRIC}} \frac{\text{Area}_{\ell',k}}{\sum_{\ell'' \in \text{BRIC}} \text{Area}_{\ell'',k}} \times \text{CPPMismatch}_{k,\ell,\ell'} \tag{19}$$

We then compare a world in which BRIC has emerged as new technology leaders to the observed equilibrium, in which technology development is concentrated disproportionately in the US and a handful of European countries.

We find that the "rise of BRIC" in global biotechnology increases average global productivity by 29.2% (Figure 11(a)), due to the fact that the BRIC countries span more ecological diversity than the existing technological leaders. Africa and parts of Asia stand particularly to gain, on average, from this realignment. However, there are also clear losers in Europe and Asia. From the perspective of the developing world, a shift of innovation investment to the BRIC nations may be a partial, if

[21] For crops that are not cultivated in any BRIC country, we use the estimated leader countries from the main analysis.

Figure 11: Counterfactuals: Rise of BRIC and Climate-Induced CPP Migration



Notes: Each graph is a cross-country histogram of productivity changes across countries in the indicated counterfactual scenarios. The left scenario corresponds to a shift of biotechnological leadership to Brazil, Russia, India, and China (Section 7.4) and the right scenario corresponds to a poleward migration of crop pests and pathogens induced by climate change (Section 7.5).

incomplete, substitute for local technological investment, since BRIC countries would endogenously develop technology that is more appropriate for low and middle-income countries.

7.5 Climate Change and CPP Mass Migration

So far, we have treated ecology as immutable and allowed the location and focus of innovators to shift over time. Climate change, however, may begin to rapidly alter ecological systems over the coming decades (Parmesan and Yohe, 2003). In the context of CPPs, increases in temperature are predicted to generate systematic movement toward the poles (Bebber et al., 2013). While such movement has been limited to date, temperature change is projected to dramatically accelerate in the near future.[22] This could change the relevant "geography of innovation" by shifting the set of CPP threats and hence the focus of technological progress in each country, even if the distribution of R&D across countries remains fixed.

To study this, we use the estimates in Bebber et al. (2013) of poleward CPP movement to project CPP habitats in the year 2100.[23] We then use these data to construct mismatch with (current) technology leaders after taking into account this change in ecology.

Our model predicts that this change in ecology has an overall *positive* effect on global productivity via the inappropriate technology mechanism (Figure 11(b)). The reason is that projected CPP

[22] CPPs have moved poleward over the past 50 years by about 135 kilometers (Bebber et al., 2013).

[23] The consensus worst case scenario implies a 4.3°C increase in temperature by 2100, and hence a 700km poleward movement of CPPs on average (or approximately the distance from Tunis to Rome). We simulate poleward range spread of each pest by identifying all countries that intersect a 700km translation of all countries that presently contain the CPP, and appending these matches to the observed presence data to construct a dataset of predicted CPP presence in 2100. Finally, we include manual corrections for countries with non-contiguous territory.

range shifts tend to make the CPP composition of currently rich and poor countries more similar, coordinating global research on a shared set of threats. Our analysis obviously does *not* account for the other presumably detrimental effects of temperature change and invasive species. However, it highlights how endogenous technological change may partially offset future ecological disruption, even in developing countries. Understanding the interactions between climate change, ecosystem shifts, and agricultural research remains an important topic for future research.

8. Conclusion

This paper investigates a long-standing hypothesis that global patterns of technology diffusion and productivity are shaped by the uneven focus of innovation. New technology—which is often designed to match the characteristics, conditions, and demands of high-income markets—may be "inappropriate" in large parts of the world, potentially explaining part of the vast global disparities in technology transfer and productivity.

We study this hypothesis in the context of global agriculture. To do so, we develop a novel measure of the potential inappropriateness of crop-specific technology based on mismatch in crop pest and pathogen environments. We find that agricultural innovation is concentrated on the ecological conditions of technology leaders and that ecological mismatch with these leaders substantially reduces both technology transfer and physical output. Combining these estimates with a model, we estimate that inappropriateness as captured by ecological mismatch reduces global agricultural productivity by 58%, and increases global disparities in productivity by 15%. Together, these results highlight that the direction of innovation—much of which takes place in a small set of high-income countries—helps sustain large disparities in global agricultural productivity.

While our findings suggest that there may be benefits to "spreading innovation out" across the world, our estimates do not take into account the heterogeneous costs of conducting R&D in different parts of the world and on different applications. Measuring both private costs and *social* costs, which may be substantially different in the presence of large research externalities, would be important for designing efficient policy interventions. Moreover, ongoing changes in global development and the environment may partially offset the need for local innovation in each market. As we show, the growth of R&D investment in large emerging markets, which are more ecologically similar to the poorest countries than the current set of technology leaders, may endogenously generate more appropriate technologies for the world's poorest farmers. That said, the dependencies generated by these technology linkages—both in the existing equilibrium and in the future—could have major implications for geopolitics and soft power, especially with mounting threats to food production due to climate change. These all strike us as important areas for future work.

References

Access to Seeds Foundation (2019). Access to Seeds Index: 2019 Synthesis Report. Accessed from: https://www.accesstoseeds.org/media/publications/.

Acemoglu, D. and Dell, M. (2010). Productivity differences between and within countries. *American Economic Journal: Macroeconomics*, 2(1):169–88.

Acemoglu, D. and Zilibotti, F. (2001). Productivity differences. *The Quarterly Journal of Economics*, 116(2):563–606.

Adamopoulos, T. and Restuccia, D. (2022). Geography and agricultural productivity: Cross-country evidence from micro plot-level data. *The Review of Economic Studies*, 89(4):1629–1653.

Atkin, D., Chaudhry, A., Chaudry, S., Khandelwal, A. K., and Verhoogen, E. (2017). Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan. *The Quarterly Journal of Economics*, 132(3):1101–1164.

Atkinson, A. B. and Stiglitz, J. E. (1969). A new view of technological change. *The Economic Journal*, 79(315):573–578.

Bandiera, O. and Rasul, I. (2006). Social networks and technology adoption in northern Mozambique. *The Economic Journal*, 116(514):869–902.

Barro, R. and Sala-i Martin, X. (1997). Technological diffusion, convergence, and growth. *Journal of Economic Growth*, 2(1):1–26.

Basu, S. and Weil, D. N. (1998). Appropriate technology and growth. *The Quarterly Journal of Economics*, 113(4):1025–1054.

Bebber, D. P., Holmes, T., Smith, D., and Gurr, S. J. (2014). Economic and physical determinants of the global distributions of crop pests and pathogens. *New Phytologist*, 202(3):901–910.

Bebber, D. P., Ramotowski, M. A., and Gurr, S. J. (2013). Crop pests and pathogens move polewards in a warming world. *Nature Climate Change*, 3(11):985–988.

Belloni, A., Chernozhukov, V., and Hansen, C. (2014). High-dimensional methods and inference on structural and treatment effects. *Journal of Economic Perspectives*, 28(2):29–50.

Bento, J. (1999). Perdas por insetos na agricultura. *Ação Ambiental*, 4(2):19–21.

Bessin, R. (2019). Bt-corn: What it is and how it works. Entfact 130, University of Kentucky College of Agriculture, Food and Environment. https://entomology.ca.uky.edu/ef130.

Bloom, D. E. and Sachs, J. D. (1998). Geography, demography, and economic growth in Africa. *Brookings Papers on Economic Activity*, 1998(2):207–295.

Boppart, T., Kiernan, P., Krusell, P., and Malmberg, H. (2023). The macroeconomics of intensive agriculture. Working Paper w31101, National Bureau of Economic Research.

Boroush, M. (2020). Research and development: U.S. trends and international comparisons. Science and Engineering Indicators Report NSB-2020-3, National Science Foundation (NSF).

Bustos, P., Caprettini, B., and Ponticelli, J. (2016). Agricultural productivity and structural transformation: Evidence from Brazil. *American Economic Review*, 106(6):1320–1365.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of Economic Growth*, 1:679–741.

Caselli, F. and Coleman II, W. J. (2006). The world technology frontier. *American Economic Review*, 96(3):499–522.

Caselli, F. and Wilson, D. J. (2004). Importing technology. *Journal of Monetary Economics*, 51(1):1–32.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption: making the theories face the facts. *Journal of Monetary Economics*, 51(1):39–83.

Comin, D. and Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5):2031–59.

Comin, D. and Mestieri, M. (2014). Technology diffusion: Measurement, causes, and consequences. In *Handbook of Economic Growth*, volume 2, pages 565–622. Elsevier.

Comin, D. and Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? *American Economic Journal: Macroeconomics*, 10(3):137–78.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1):35–69.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248.

De Groote, H. (2002). Maize yield losses from Stemborers in Kenya. *Insect Science and Its Application*, 22(2):89–96.

Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N., and Ménière, Y. (2011). Invention and transfer of climate change–mitigation technologies: a global analysis. *Review of Environmental Economics and Policy*.

Diamond, J. (1997). *Guns, Germs, and Steel: the Fates of Human Societies*. WW Norton & Company, New York.

Dong, O. X. and Ronald, P. C. (2019). Genetic engineering for disease resistance in plants: recent progress and future perspectives. *Plant Physiology*, pages 26–38.

Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, 101(6):2350–90.

Evenson, R. E. and Gollin, D. (2003a). Assessing the impact of the Green Revolution, 1960 to 2000. *Science*, 300(5620):758–762.

Evenson, R. E. and Gollin, D., editors (2003b). *Crop variety improvement and its effect on productivity*. CABI Publishing, Cambridge, MA, USA.

Fernandez-Cornejo, J. and Caswell, M. (2006). The first decade of genetically engineered crops in the united states. Economic Information Bulletin 11, USDA Economic Research Service.

Fuglie, K. O. (2012). Productivity growth and technology capital in the global agricultural economy. In Fuglie, K. O., Wang, S. L., and Ball, E., editors, *Productivity Growth in Agriculture: An International Perspective*, pages 335–368. CABI, Wallingford, UK.

Fuglie, K. O. (2016). The growing role of the private sector in agricultural research and development world-wide. *Global Food Security*, 10:29–38.

Galitsky, N., Cody, V., Wojtczak, A., Ghosh, D., Luft, J. R., Pangborn, W., and English, L. (2001). Structure of the insecticidal bacterial δ-endotoxin Cry3Bb1 of Bacillus thuringiensis. *Acta Crystallographica Section D: Biological Crystallography*, 57(8):1101–1109.

Gallup, J. L., Sachs, J. D., and Mellinger, A. D. (1999). Geography and economic development. *International Regional Science Review*, 22(2):179–232.

Gates, B. (2009). Prepared Remarks for 2009 World Food Prize Symposium. Retrieved from: https://www.gatesfoundation.org/ideas/speeches/2009/10/bill-gates-2009-world-food-prize-symposium.

Giorcelli, M. (2019). The long-term effects of management and technology transfers. *American Economic Review*, 109(1):121–52.

Gollin, D., Lagakos, D., and Waugh, M. E. (2014). The agricultural productivity gap. *The Quarterly Journal of Economics*, 129(2):939–993.

Gray, M. E., Sappington, T. W., Miller, N. J., Moeser, J., and Bohn, M. O. (2009). Adaptation and invasiveness of Western Corn Rootworm: intensifying research on a worsening pest. *Annual Review of Entomology*, 54:303–321.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica*, 25(4):501–522.

Herrera-Estrella, L. and Alvarez-Morales, A. (2001). Genetically modified crops: hope for developing countries? *EMBO Reports*, 2(4):256–258.

Hotez, P. J., Molyneux, D. H., Fenwick, A., Kumaresan, J., Sachs, S. E., Sachs, J. D., and Savioli, L. (2007). Control of neglected tropical diseases. *New England Journal of Medicine*, 357(10):1018–1027.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *the Quarterly journal of Economics*, 108(3):577–598.

Jost, L., Chao, A., and Chazdon, R. L. (2011). Compositional similarity and β (beta) diversity. In Magurran, A. E. and McGill, B. J., editors, *Biological Diversity: Frontiers in Measurement and Assessment*, pages 66–84. Oxford University Press, New York.

Kamarck, A. M. (1976). *The tropics and economic development*. The John Hopkins University Press, Baltimore, MD, USA.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3):752–782.

Kremer, M. and Glennerster, R. (2004). *Strong Medicine: Creating Incentives for Pharmaceutical Research on Neglected Diseases*. Princeton University Press.

Lansing, J. S. (2009). *Priests and programmers: technologies of power in the engineered landscape of Bali*. Princeton University Press.

Liu, E. and Ma, S. (2023). Innovation Networks and R&D Allocation. Technical report, National Bureau of Economic Research.

Marenya, P. P. and Barrett, C. B. (2009). Soil quality and fertilizer use rates among smallholder farmers in Western Kenya. *Agricultural Economics*, 40(5):561–572.

McMullen, N. (1987). Seeds and world agricultural progress. Report 227, National Planning Association.

Moscona, J. and Sastry, K. A. (2023). Does directed innovation mitigate climate damage? evidence from us agriculture. *The Quarterly Journal of Economics*, 138(2):637–701.

Moseman, A. H. (1970). *Building agricultural research systems in the developing countries.* Agricultural Development Council, New York.

Munkvold, G. P. and Hellmich, R. L. (1999). Genetically modified insect resistant corn: Implications for disease management. *APSnet Plant Pathology On-line Feature*, 15.

Nordhaus, H. (2017). Cornboy vs. the Billion-Dollar Bug. *Scientific American*, 316(3):64–71.

Oerke, E.-C. and Dehne, H.-W. (2004). Safeguarding production—losses in major crops and the role of crop protection. *Crop Protection*, 23(4):275–285.

Olmstead, A. L. and Rhode, P. W. (2008). *Creating Abundance: Biological Innovation and American Agricultural Development*. Cambridge University Press, New York.

Olmstead, A. L. and Rhode, P. W. (2011). Adapting North American wheat production to climatic challenges, 1839–2009. *Proceedings of the National Academy of sciences*, 108(2):480–485.

Parente, S. L. and Prescott, E. C. (1994). Barriers to technology adoption and development. *Journal of Political Economy*, 102(2):298–321.

Parente, S. L. and Prescott, E. C. (2002). *Barriers to Riches*. MIT Press.

Parmesan, C. and Yohe, G. (2003). A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, 421(6918):37–42.

Pasiecznik, N., Smith, I., Watson, G., Brunt, A., Ritchie, B., and Charles, L. (2005). CABI/EPPO distribution maps of plant pests and plant diseases and their important role in plant quarantine. *EPPO Bulletin*, 35(1):1–7.

Pingali, P. L. (2012). Green revolution: impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, 109(31):12302–12308.

Reynolds, M. P. and Borlaug, N. (2006). Impacts of breeding on international collaborative wheat improvement. *The Journal of Agricultural Science*, 144(1):3–17.

Rossi, F. (2022). The relative efficiency of skilled labor across countries: Measurement and interpretation. *American Economic Review*, 112(1):235–66.

Ruttan, V. W. and Hayami, Y. (1973). Technology transfer and agricultural development. *Technology and Culture*, 14(2):119–151.

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., and Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, 3(3):430–439.

Shaw, M. W. and Osborne, T. M. (2011). Geographic distribution of plant pathogens in response to climate change. *Plant Pathology*, 60(1):31–43.

Stewart, F. (1978). *Technology and Underdevelopment*. MacMillan, London, UK.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209.

Suri, T. and Udry, C. (2022). Agricultural technology in Africa. *Journal of Economic Perspectives*, 36(1):33–56.

Van Esse, H. P., Reuber, T. L., and van der Does, D. (2020). Genetic modification to improve disease resistance in crops. *New Phytologist*, 225(1):70–86.

Vanderplank, J. E. (2012). *Disease Resistance in Plants*. Academic Press, Orlando, FL, USA.

Verhoogen, E. (2021). Firm-level upgrading in developing countries. Working Paper 29461, National Bureau of Economic Research.

Walker, T. S. and Alwang, J. (2015). *Crop improvement, adoption, and impact of improved varieties in food crops in sub-Saharan Africa*. CABI.

Appendix for
"Inappropriate Technology: Evidence from Global Agriculture"
by Moscona and Sastry

Contents

A. Proofs

A.1 Supplementary Lemmas

We first provide two results that assist in proving Propositions 1, 2, and 3.

Lemma 1. *Consider a farmer with production function $f(X) = (X)^{1-\gamma}(\theta\omega\varepsilon)^{\gamma}$, who can purchase the input X at price q, and sell their output at price p. Their profit is*

$$\Pi = \gamma \left(\frac{1-\gamma}{q}\right)^{\frac{1-\gamma}{\gamma}} p^{\frac{1}{\gamma}} \theta\omega\varepsilon \tag{20}$$

Proof. Farmers choose the input quantity to solve:

$$\Pi = \max_X \left\{ p(X)^{1-\gamma}(\theta\omega\varepsilon)^{\gamma} - qX \right\} \tag{21}$$

This is a strictly concave problem. The first-order condition is $0 = (1-\gamma)p(\theta\omega\varepsilon)^{\gamma}(X)^{-\gamma} - q$. Rearranging and substituting into Equation 21 yields Equation 20. □

Lemma 2. *The measure of farmers planting crop k in country ℓ is*

$$\pi_{k,\ell} = \frac{p_k^{\frac{\eta}{\gamma}} q_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k,\ell}^{\eta} \omega_{k,\ell}^{\eta}}{\sum_{k'} p_{k'}^{\frac{\eta}{\gamma}} q_{k',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k',\ell}^{\eta} \omega_{k',\ell}^{\eta}} \tag{22}$$

Moreover, the expected profit of farmers conditional on any choice is

$$\Xi_\ell = \gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}} \left(\sum_{k=1}^{K} p_k^{\frac{\eta}{\gamma}} q_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k,\ell}^{\eta} \omega_{k,\ell}^{\eta} \right)^{\frac{1}{\eta}} \tag{23}$$

Proof. Let $k_{i,\ell}^* \in \{1, \ldots, K\}$ denote the crop-technology choice of farmer i in country ℓ and define

$$\nu_{k,\ell} = \gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}} p_k^{\frac{1}{\gamma}} q_{k,\ell}^{-\frac{1-\gamma}{\gamma}} \omega_{k,\ell}\theta_{k,\ell} \tag{24}$$

Let $F(z)$ denote the cumulative distribution function of a Fréchet random variable with scale one and shape parameter $\eta > 1$, or $F(z) = \exp(-x^{-\eta})$. Since $\varepsilon_{i,k,\ell}$ is Fréchet with mean one and shape $\eta > 1$, its scale parameter is $s = (\Gamma(1-1/\eta))^{-1}$; thus the normalized shock $\hat{\varepsilon}_{i,k,\ell} = \frac{1}{s}\varepsilon_{i,k,\ell}$ is distributed by $F(z)$. Due to a law of large numbers across draws of the shock, $\pi_{k,\ell} = \mathbb{P}[k_{i,\ell}^* = k]$.

If a farmer draws $\hat{\varepsilon}_{i,k,\ell} = z$, then that farmer chooses k if this results in the maximum productivity among all options, or $\nu_{k,\ell} z > \nu_{k',\ell}\hat{\varepsilon}_{i,k',\ell}$ for all other k'. These events are independent across all k'. Thus the probability of choosing k is given by the probability of the event described above, conditional on each realization z, integrated over the distribution of z:

$$\begin{aligned}\pi_{k,\ell} &= \int_0^\infty \prod_{k \neq k} F\left(\frac{\nu_{k,\ell}}{\nu_{k',\ell}} z\right) \mathrm{d}F(z) \\ &= \int_0^\infty \left(\prod_{k' \neq k} \exp\left(-\left(\frac{\nu_{k,\ell}}{\nu_{k',\ell}} z\right)^{-\eta}\right)\right) \eta z^{-1-\eta} \exp(-z^\eta)\,\mathrm{d}z = \int_0^\infty \eta \exp\left(-z^{-\eta} \frac{\Xi_\ell^\eta}{\nu_{k,\ell}^{-\eta}}\right) z^{-1-\eta}\,\mathrm{d}z\end{aligned} \tag{25}$$

where in the second equality we substituted the expression for $F(z)$ in the third equality we defined the productivity index $\Xi_\ell = \left(\sum_{k=1}^K \nu_{k,\ell}^\eta\right)^{1/\eta}$. After a change in variables in the integrand to $\tilde{z} = z\frac{\nu_{k,\ell}}{\Xi_\ell}$, the original integral can be re-written and simplified as

$$\pi_{k,\ell',\ell} = \frac{\nu_{k,\ell',\ell}^\eta}{\sum_{k',\ell''} \nu_{k',\ell'',\ell}^\eta} \int_0^\infty \eta \exp\left(-\tilde{z}^{-\eta}\right) \tilde{z}^{-1-\eta}\,\mathrm{d}z = \frac{\nu_{k,\ell',\ell}^\eta}{\sum_{k',\ell''} \nu_{k',\ell'',\ell}^\eta} \int_0^\infty \mathrm{d}F(\tilde{z}) = \frac{\nu_{k,\ell',\ell}^\eta}{\sum_{k',\ell''} \nu_{k',\ell'',\ell}^\eta} \tag{26}$$

Re-writing the last equality with the definition of $\nu_{k,\ell}$ completes the derivation of Equation 22.

We next derive profitability of production conditional on a given crop choice. Let

$$V_{i,\ell}^* = \max_{k'} \left\{\nu_{k',\ell} \varepsilon_{i,k',\ell}\right\} \tag{27}$$

denote the profitability of farmer i in country ℓ evaluated at the optimal choice. The probability that $V_{i,\ell}^*$ is less than some value v, conditional on the optimal crop choice being k, can be obtained by integrating the right-hand-side of Equation 25 up to the realization $\frac{v}{s\nu_{k,\ell}}$, and normalizing by the probability of choosing k':

$$\mathbb{P}[V_{i,\ell}^* \leq v \mid k_{i,\ell}^* = k] = \frac{1}{\pi_{k,\ell}} \int_0^{\frac{v}{s\nu_{k,\ell}}} \prod_{k' \neq k} F\left(\frac{\nu_{k,\ell}}{\nu_{k',\ell}} z\right) \mathrm{d}F(z) = \int_0^{\frac{v}{s\Xi_\ell}} \mathrm{d}F\left(\tilde{z}\right) \tag{28}$$

where the second equality changes variables in the integrand to $\tilde{z} = z\frac{\nu_{k,\ell',\ell}}{\Xi_\ell}$. This implies that $V_{i,\ell}^*$ conditional on $k_{i,\ell}^* = k$ can be written as the product of Ξ_ℓ and a unit-mean Fréchet random variable, regardless of the k. Thus, $\mathbb{E}[V_{i,\ell}^* | k_{i,\ell}^* = k] = \Xi_\ell, \forall k$. This implies the desired claim, after substituting in the expression for Ξ_ℓ.

□

A.2 Proof of Proposition 1

Under the maintained assumption that $B_{t,k,\ell} = \bar{B}$ if $t \in \mathcal{T}_{k,L}$ and $\underline{B}$ otherwise, we have that

$$\begin{aligned}\log\theta_{k,\ell} &= \alpha \log A_k + \frac{1-\alpha}{T} \sum_{t \in \mathcal{T}_{k,\ell}} \left(\log \bar{B} \cdot \mathbb{I}_{t \in \mathcal{T}_{k,L}} + \log \underline{B} \cdot \mathbb{I}_{t \notin \mathcal{T}_{k,L}}\right) \\ &= \alpha \log A_k + (1-\alpha)\bar{B} - \delta_{k,\ell,L}(1-\alpha)(\log \bar{B} - \log \underline{B})\end{aligned} \tag{29}$$

where the last line uses the definition of ecological mismatch, $\delta_{k,\ell,L} = 1 - \frac{1}{T}|\mathcal{T}_{k,\ell} \cap \mathcal{T}_{k,L}|$.

Using constant expenditure and profit shares (under Cobb-Douglas production), we derive the quantity of inputs demanded for farmers of crop k in location ℓ as $X_{k,\ell} = \frac{1-\gamma}{q_{k,\ell}\gamma}\Xi_\ell \pi_{k,\ell}$. Substituting in for Ξ_ℓ and $\pi_{k,\ell}$ using the result of Lemma 2 and substituting for $q_{k,\ell} = C_\ell$ using the limit-pricing assumption gives

$$X_{k,\ell} = \gamma^{\eta-1}(1-\gamma)^{1+\eta\frac{1-\gamma}{\gamma}} C_\ell^{-\eta\frac{1-\gamma}{\gamma}} \Xi_\ell^{1-\eta} p_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} \theta_{k,\ell}^{\eta} \tag{30}$$

Finally, taking logs and substituting in Equation 29, we write

$$\log X_{k,\ell} = -\beta \cdot \delta_{k,\ell,L} + \chi_{k,\ell} + \chi_{k,L} + \chi_{\ell,L} \tag{31}$$

where $\beta = \eta(1-\alpha)(\log \bar{B} - \log \underline{B}) \geq 0$ and one representation of the fixed effects is

$$\begin{aligned}
\chi_{k,\ell} &= \eta \log \omega_{k,\ell} + (1-\eta)\log \Xi_\ell \\
\chi_{k,L} &= \alpha \log A_k + (1-\alpha)\log \bar{B} + \frac{\eta}{\gamma}\log p_k \\
\chi_{\ell,L} &= -\eta\frac{1-\gamma}{\gamma}\log C_\ell + (\eta-1)\log\gamma + (1+\eta)\frac{1-\gamma}{\gamma}\log(1-\gamma)
\end{aligned} \tag{32}$$

A.3 Proof of Proposition 2

As derived in Lemma 1, physical production on farm i conditional on planting (k,ℓ') is

$$Y_{i,k,\ell} = \left(\frac{1-\gamma}{q_{k,\ell}}\right)^{\frac{1-\gamma}{\gamma}} p_k^{\frac{1}{\gamma}-1}\theta_{k,\ell}\omega_{k,\ell}\varepsilon_{k,i} = \frac{\Pi_{i,k,\ell}}{\gamma p_k} \tag{33}$$

where $\Pi_{i,k,\ell}$ is the profit earned by the farmer. Applying a law of large numbers over the realization of shocks $\varepsilon_{i,k,\ell}$, total production is the sum of expected production:

$$Y_{k,\ell} = \mathbb{E}\left[\frac{V_{i,\ell}^*}{\gamma p_k} \mid k_{i,\ell}^* = k\right] \cdot \pi_{k,\ell} \tag{34}$$

As shown in Lemma 2, $\mathbb{E}\left[V_{i,\ell}^* \mid k_{i,\ell}^* = k\right] = \Xi_\ell$ for any (k,ℓ'). Thus,

$$\begin{aligned}
Y_{k,\ell} &= \frac{1}{\gamma p_k}\Xi_\ell\pi_{k,\ell} = \frac{1}{\gamma p_k}\Xi_\ell\left(\theta_{k,\ell}^{\eta}\omega_{k,\ell}^{\eta}p_k^{\frac{\eta}{\gamma}}\Xi_\ell^{-\eta}\gamma^{\eta}(1-\gamma)^{\eta\frac{1-\gamma}{\gamma}}(q_{k,\ell})^{-\eta\frac{1-\gamma}{\gamma}}\right) \\
&= \gamma^{\eta-1}(1-\gamma)^{\eta\frac{1-\gamma}{\gamma}}C_\ell^{-\eta\frac{1-\gamma}{\gamma}}p_k^{\frac{\eta}{\gamma}-1}\Xi_\ell^{1-\eta}\omega_{k,\ell}^{\eta}\theta_{k,\ell}^{\eta} \\
&= \gamma^{\eta-1}(1-\gamma)^{\eta\frac{1-\gamma}{\gamma}}C_\ell^{-\eta\frac{1-\gamma}{\gamma}}p_k^{\frac{\eta}{\gamma}-1}\Xi_\ell^{1-\eta}\omega_{k,\ell}^{\eta}A_k^{\alpha\eta}\bar{B}^{(1-\alpha)\eta}e^{-\eta(1-\alpha)\delta_{k,\ell,L}(\log\bar{B}-\log\underline{B})}
\end{aligned} \tag{35}$$

where the second equality in the first substitutes the expression for $\pi_{k,\ell',\ell}$ derived in Lemma 2, the second line collects terms and simplifies $q_{k,\ell',\ell} = C_\ell$, and the third line substitutes in the expression for $\theta_{k,\ell}$ from Equation 29.

Taking a log, we obtain the desired expression

$$\log Y_{k,\ell} = -\beta \log \delta_{k,\ell,L} + \chi_k + \chi_\ell + \eta \log \omega_{k,\ell} \tag{36}$$

where $\beta = \eta(1-\alpha)(\log \bar{B} - \log \underline{B}) \geq 0$ and one representation of the fixed effects is

$$\begin{aligned} \chi_k &= \left(\frac{\eta}{\gamma} - 1\right) \log p_k + \eta\alpha \log A_k \\ \chi_\ell &= (1-\eta) \log \Xi_\ell + \eta(1-\alpha) \log \bar{B} + (\eta - 1) \log \gamma + \eta \frac{1-\gamma}{\gamma} (\log(1-\gamma) - \log C_\ell) \end{aligned} \tag{37}$$

We can also derive analogous expressions for planted area and physical yield. First, by inspection of Equation 35, we observe that

$$\log \pi_{k,\ell} = \log Y_{k,\ell} - \log \Xi_\ell + \log p_k + \log \gamma \tag{38}$$

and hence can be written in the same fixed-effects-regression form. Finally, observe that physical yield $z_{k,\ell}$ equals production per unit area. Thus

$$\log z_{k,\ell} = \log Y_{k,\ell} - \log \pi_{k,\ell} = \log \Xi_\ell - \log p_k - \log \gamma \tag{39}$$

A.4 Proof of Proposition 3

This follows immediately from combining the expression for $\theta_{k,\ell}$ given in Equation 29 with the definition of Ξ_ℓ in Equation 23 (Lemma 2), observing that $q_{k,\ell} = C_\ell$ by the limit-pricing assumption, and defining

$$\chi = \log \gamma + \frac{1-\gamma}{\gamma} \log(1-\gamma) + (1-\alpha) \log \bar{B} \tag{40}$$

A.5 Mapping to Multiple-Input Model

Here, we show how a variant model with multiple inputs maps to our main model. Departing from the baseline, the farm has a new production function that uses $N+1$ inputs. The production function, suppressing dependence on the index i and crop k for convenience, is

$$Y = X^{1-\gamma-\sum_{n=1}^{N} \alpha_n} \left(\prod_{n=1}^{N} X_n^{\alpha_n} \right) (\theta \tilde{\omega} \varepsilon)^\gamma \tag{41}$$

where $\gamma \in (0,1)$ continues to measure the return to fixed factors versus technology; $\tilde{\omega} \in \mathbb{R}_+$ is average natural suitability; $\varepsilon \in \mathbb{R}_+$ is an idiosyncratic perturbation with a Fréchet distribution with mean one and shape parameter $\eta > 0$; the α_n are the returns to scale for each additional input; X is usage of the biotechnological input; and the X_n are the usage of other inputs. We assume that $0 < \gamma + \sum_{n=1}^{N} \alpha_n < 1$, so there are decreasing returns to scale in the variable factors. The farm faces price $\tilde{q}$ for the biotechnological input and $\tilde{q}_n$ for the other inputs. Its input-choice profit maximization problem is

$$\max_{X,(X_n)_{n=1}^N} \left\{ pX^{1-\gamma-\sum_{n=1}^N \alpha_n} \left(\prod_{n=1}^N X_n^{\alpha_n} \right) (\theta \tilde{\omega} \varepsilon)^\gamma - \tilde{q} X - \sum_{n=1}^N \tilde{q}_n X_n \right\} \tag{42}$$

We now show a one-to-one mapping between this variant model and our baseline model:

Lemma 3. *The multiple-input model implies the same farm-level profits as the one-input model where*

$$\begin{aligned} q &= \tilde{q}^{\frac{1-\gamma-\sum_{n=1}^N \alpha_N}{1-\gamma}} \\ \omega &= \tilde{\omega} K(\alpha,\gamma)^{\frac{1}{\gamma}} \left(\prod_{n=1}^N q_n^{-\alpha_n} \right) \end{aligned} \tag{43}$$

and $K(\alpha,\gamma) = (1-\gamma-\sum_{n=1}^N \alpha_n)^{1-\gamma-\sum_{n=1}^N \alpha_n} \prod_{n=1}^N \alpha_n^{\alpha_n}$. *Given this mapping, the multiple-input and one-input models therefore have the same implications for aggregate technology development, technology transfer, production, and productivity.*

Proof. The first-order condition for the inputs can be re-arranged to

$$X = \frac{(1-\gamma-\sum_{n=1}^N \alpha_n) pY}{q} \qquad X_n = \frac{\alpha_n pY}{q_n} \forall n \tag{44}$$

Substituting these choices into the production function and solving for Y, we find

$$Y = \frac{K(\alpha,\gamma)^{\frac{1}{\gamma}} \theta \omega \varepsilon p^{\frac{1-\gamma}{\gamma}}}{q^{\frac{1-\gamma-\sum_{n=1}^N \alpha_n}{\gamma}} \prod_{n=1}^N q_n^{\alpha_n}} \tag{45}$$

where $K(\alpha,\gamma) = (1-\gamma-\sum_{n=1}^N \alpha_n)^{1-\gamma-\sum_{n=1}^N \alpha_n} \prod_{n=1}^N \alpha_n^{\alpha_n}$. The profits of the farmer are share γ of total revenues, or

$$\Pi = \gamma p Y = \gamma \cdot \left(p^{\frac{1}{\gamma}} q^{-\frac{1-\gamma-\sum_{n=1}^N \alpha_n}{\gamma}} \left(\prod_{n=1}^N q_n^{-\alpha_n} \right) K(\alpha,\gamma)^{\frac{1}{\gamma}} \theta \omega \varepsilon \right) \tag{46}$$

Comparing this expression to Equation 20 in Lemma 2, which derived farmer profits in the main model, we see that the models are isomorphic under the transformation described by Equation 43. The transformed productivity incorporates the (inverse) price of the other inputs into our measure of crop-by-location level productivity.

The last claim follows from recognizing that all of this paper's results characterizing technology development, technology transfer, production, and productivity depend on farmers' behavior only through profit function and input demand derived in Lemma 1. □

B. Extended Model

In this Appendix, we describe a model that generalizes our baseline model (Section 2) along five dimensions: (i) multiple countries can innovate; (ii) innovators can determine both context-neutral ("A") and context-specific ("B") components of technology; (iii) innovators can improve these attributes along an intensive margin; (iv) innovators can have noisy expectations of seed demand; and (v) farmers face input-adoption wedges. In this model, we derive analogs to our main theoretical results, which motivate our empirical strategies.

B.1 Set-up

Production. As in the main model, there is a set of countries $\ell \in \{1, \ldots, L\}$ and a set of crops indexed by $k \in \{1, \ldots, K\}$. In each country, there is a continuum of farms indexed by $i \in [0, 1]$. Each farm can produce any of the K crops. Differently from the main model, for each crop there are L distinct technologies which come from different origin countries. A farm i in country ℓ, planting crop k, and using technology from country ℓ' produces output

$$(X_{i,k,\ell',\ell})^{1-\gamma}(\theta_{k,\ell',\ell}\omega_{k,\ell}\varepsilon_{i,k,\ell',\ell})^{\gamma} \tag{47}$$

where X denotes the quantity of technology used, θ denotes the *origin-by-destination-by-crop* specific quality, ω denotes local suitability, and ε denotes a *origin-by-destination-by-crop* specific Fréchet-distributed shock with mean one and shape parameter η. Farmers in country ℓ choose what crop to grow, *from where* to source their technology, and how much of the input to buy, taking as given output prices p_k and input prices $q_{k,\ell',\ell}$. Finally, in technology input markets, farmers in country ℓ face *wedges* that distort their technology choice. That is, when making choices, farmers behave *as if* the price of technology is $q_{k,\ell',\ell}\zeta_{k,\ell}$, where $\zeta_{k,\ell} > 1$ encodes the possibility that technology is (as-if) taxed in a particular country. The existence of such wedges is consistent with the "barriers to riches" hypothesis of Parente and Prescott (1994).

Environmentally Adapted Technology. Environmental characteristics are modeled exactly as in the baseline model. That is, $\mathcal{T}_{k,\ell} \subset \mathbb{N}$ denotes the characteristics of the (k, ℓ) ecosystem. The quality of crop-k technology from ℓ', employed in country ℓ, is

$$\theta_{k,\ell',\ell} = \exp\left(\alpha \log A_{k,\ell'} + \frac{1-\alpha}{T} \sum_{t \in \mathcal{T}_{k,\ell}} \log B_{t,k,\ell',\ell}\right) \tag{48}$$

where we observe that environmental adaptations are now specific to origins and destinations.

Endogenous Innovation. A representative innovator in each country ℓ' can develop technology for each country ℓ and crop k. To develop characteristic $B_{t,k,\ell',\ell}$, innovators face convex research costs with an uninternalized knowledge spillover from local research on the same CPP:

$$C_{k,\ell',t}(B) = e^{-\tau(B_{t,k,\ell',\ell'})} \frac{(B_{0,\ell'}B)^{1+\phi}}{T(1+\phi)} \tag{49}$$

where $\phi > 0$ is an inverse elasticity of research supply, $B_{0,\ell'} > 0$ is a country-specific constant, and the function $\tau : \mathbb{R}_+ \to \mathbb{R}_+$, which is increasing and satisfies $\tau(0) = 0$, controls the knowledge spillover.[24] The spillover may capture nonrival inputs like knowledge about local conditions or genetic sequences. This aspect of agricultural technology development is well-documented in the context of private-sector, public-sector, and philanthropically supported research. For example, Kantor and Whalley (2019) document local productivity spillovers of US-government research stations and discuss the role of knowledge and input diffusion, Reynolds and Borlaug (2006) discuss the importance of local germplasm and test fields at the non-profit CIMMYT, and Duvick et al. (2004) highlights the importance of similar inputs for maize breeding at Pioneer Hi-Bred.

To develop the general characteristic $A_{k,\ell'}$, the innovator faces a convex R&D cost $K_{k,\ell'}(A)$, where K is a potentially crop-and-origin-specific function. We finally, as in the main analysis, study the case in which the price of technology is pinned down as C_ℓ in destination ℓ by a competitive fringe of copycat producers.

Innovators in each country ℓ' choose, for each (k, ℓ) destination market, the vector of R&D spending to maximize revenues net of costs, given the pricing policy described above and conjectures for crop prices, the destination's productivity, and local research on each CPP. That is, for each crop, the country ℓ' innovator solves the problem

$$\max_{A_{k,\ell'}, \vec{B}_{k,\ell',\ell}} \left\{ e^{-\rho_{\ell',\ell}} \hat{R}(\vec{B}_{k,\ell',\ell}; \hat{p}_k, \hat{\Xi}_\ell, q_{k,\ell',\ell}) - \sum_{t\in\mathcal{T}_{k,\ell}} e^{-\tau(\hat{B}_{t,k,\ell',\ell'})} \frac{(B_{0,\ell'}B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)} \right\} \tag{50}$$

where $\hat{R}(\cdot)$ gives the innovator's conjecture for net revenue from technology sales, $\hat{p}_k$ is the conjecture of prices, $\hat{\Xi}_\ell$ is the conjecture of productivity, and $\hat{B}_{t,k,\ell',\ell'}$ is, for each t, the conjecture of local CPP-specific research.

We finally allow for the possibility that innovators in location ℓ have idiosyncratic expectations of seed demand by leaving the expectations of crop prices and agricultural productivity as free parameters. The case of full-information rational expectations is nested when $\hat{Z} = Z$ for all equilibrium variables Z.

B.2 Toward the Model's Predictions: Production, Technology Demand, and Research

Toward deriving analogs to our main model predictions (cf. Section 2.2), we first describe farmers' behavior conditional on technology availability. From Lemma 1, the profit of a farmer i in

[24] We assume that $\phi > (1-\alpha)\eta - 1$, which is sufficient for the innovator's problem for choosing research levels has an interior solution.

country ℓ conditional on choosing technology-crop pair ℓ', k is

$$\Pi_{i,k,\ell',\ell} = \gamma \left(\frac{1-\gamma}{q_{k,\ell',\ell}} \right)^{\frac{1-\gamma}{\gamma}} p_k^{\frac{1}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{i,k,\ell',\ell} \tag{51}$$

While in the main analysis the farmer's choice problem was only over crops k (see Lemma 2), here the choice is over pairs (k, ℓ'). Nonetheless, the exact same arguments suffice to show that the measure of farmers planting crop k and using technology from ℓ' in country ℓ is

$$\pi_{k,\ell',\ell} = \frac{p_k^{\frac{\eta}{\gamma}} q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \zeta_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k,\ell'\ell}^{\eta} \omega_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''} p_{k'}^{\frac{\eta}{\gamma}} q_{k',\ell'',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \zeta_{k',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k',\ell'',\ell}^{\eta} \omega_{k',\ell}^{\eta}} \tag{52}$$

And, moreover, the expected profit of farmers conditional on any choice is

$$\Xi_\ell = \gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}} \left(\sum_{k,\ell'} p_k^{\frac{\eta}{\gamma}} q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \zeta_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell}^{\eta} \omega_{k,\ell}^{\eta} \right)^{\frac{1}{\eta}} \tag{53}$$

We next study the innovator's choice of environmentally-specific R&D investment. Total investment by crop k farmers in country ℓ on technology from country ℓ' is

$$(1-\gamma) \frac{\Pi_{i,\ell',k}}{\gamma} \pi_{k,\ell',\ell} \tag{54}$$

where the first term is the expenditure share on technology (owing to Cobb-Douglas technology with output elasticity $1-\gamma$), the second is total revenue for each farmer (owing to the fact that profits are share γ of revenues), and the last term is the measure of farmers who choose the pair (k, ℓ'). The innovator's profit margin is $(C_\ell - 1)$ per unit sold; and, because of the multiplicative wedge, fraction $1/\zeta_{k,\ell}$ of expenditure goes to the innovator. Thus, the innovator associated with market (k, ℓ') conjectures that they will receive the following revenue from the (k, ℓ) market:

$$\begin{aligned} \hat{R}_{k,\ell',\ell} &= \frac{C_\ell - 1}{\zeta_{k,\ell}} (1-\gamma) \frac{\Pi_{i,\ell',k}}{\gamma} \pi_{k,\ell',\ell} \\ &= \gamma^{\eta-1} (1-\gamma)^{1+\eta\frac{1-\gamma}{\gamma}} (C_\ell - 1) q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \zeta_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}-1} \hat{\Xi}_\ell^{1-\eta} \hat{p}_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t \in \mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} \end{aligned} \tag{55}$$

where the second line substitutes in the expressions for productivity and choice probabilities and the hats denote conjectures by the (k, ℓ') innovator.

We next study the incentives for environmentally specific innovations, from the perspective of an innovator for crop k in country ℓ'. For a non-present pest $t \notin T_{k,\ell}$, the marginal benefit of innovation is zero. Hence $B_{t,k,\ell',\ell}=0$. For a present pest $t\in T_{k,\ell'}$, the first-order condition is

$$\frac{\eta(1-\alpha)}{TB_{t,k,\ell',\ell}}\left(K_0(\gamma,\eta)K_1(C_\ell)\zeta_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}-1}e^{-\rho_{\ell',\ell}}\hat{\Xi}_\ell^{1-\eta}\hat{p}_k^{\frac{\eta}{\gamma}}\omega_{k,\ell}^{\eta}A_{k,\ell'}^{\alpha\eta}\prod_{t\in\mathcal{T}_{k,\ell}}B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}}\right)-\frac{1}{T}e^{-\tau(\hat{B}_{t,k,\ell',\ell'})}B_{0,\ell'}^{1+\phi}B_{t,k,\ell',\ell}^{\phi}=0$$

where $K_0(\gamma,\eta)=\gamma^{\eta-1}(1-\gamma)^{1+\eta\frac{1-\gamma}{\gamma}}$ is a constant depending on farmers' profit share and supply elasticity, and $K_1(C_\ell)=(C_\ell-1)C_\ell^{-\eta\frac{1-\gamma}{\gamma}}$ summarizes the effect of the markup for increasing profit margins (first term) and decreasing demand (second term). We next take logs and impose the equilibrium condition that the conjectures are correct. The first-order condition re-arranges to

$$\begin{aligned}\log B_{t,k,\ell',\ell}=&\frac{\log\left(K_0(\gamma,\eta)\eta(1-\alpha)\right)}{1+\phi}-\log B_{0,\ell'}-\frac{\rho_{\ell',\ell}}{1+\phi}+\frac{1-\eta}{1+\phi}\log\hat{\Xi}_\ell+\frac{\eta}{\gamma(1+\phi)}\log\hat{p}_k\\&+\frac{1}{1+\phi}\log K_1(C_\ell)+\frac{\eta}{1+\phi}\log\omega_{k,\ell}+\frac{\eta}{1+\phi}\log\theta_{k,\ell',\ell}+\frac{1}{1+\phi}\tau(\hat{B}_{t,k,\ell',\ell'})\\&-\frac{1}{1+\phi}\log\tilde{\zeta}_{k,\ell}+\frac{1}{1+\phi}\log\xi_{k,\ell',\ell}\end{aligned}\tag{56}$$

where we define $\log\tilde{\zeta}_{k,\ell}=(\eta(1-\gamma)\gamma^{-1}-1)\log\zeta_{k,\ell}$ as a (monotone) transformation of the wedge and $\xi_{k,\ell',\ell}$ as an *expectational error for technology demand*:

$$\log\xi_{k,\ell',\ell}=(1-\eta)(\log\hat{\Xi}_\ell-\log\Xi_\ell)+\frac{\eta}{\gamma}(\log\hat{p}_k-\log p_k)\tag{57}$$

In particular, when $\log\xi_{k,\ell',\ell}>0$ (<0), the (k,ℓ') innovator overestimates (underestimates) demand for technology in the relevant market and therefore over- (under-)invests in R&D.

We next substitute Equation 56 into the definition of $\log\theta_{k,\ell',\ell}$ (Equation 48) and re-arrange terms to write

$$\begin{aligned}\log\theta_{k,\ell',\ell}=&\frac{1}{1+\phi-\eta(1+\alpha)}\Big(\alpha\log A_{k,\ell'}+(1-\alpha)\log\left(K_0(\gamma,\eta)\eta(1-\alpha)\right)-(1-\alpha)\log B_{0,\ell'}-(1-\alpha)\rho_{\ell',\ell}\\&+(1-\alpha)(1-\eta)\log\Xi_\ell+\frac{(1-\alpha)\eta}{\gamma}\log p_k+(1-\alpha)\eta\log\omega_{k,\ell}+(1-\alpha)\log K_1(C_\ell)\\&-(1-\alpha)\log\tilde{\zeta}_{k,\ell}+(1-\alpha)\log\xi_{k,\ell',\ell}+\frac{1-\alpha}{T}\sum_{\tau\in\mathcal{T}_{k,\ell}}\tau(\hat{B}_{t,k,\ell',\ell'})\Big)\end{aligned}\tag{58}$$

We now simplify the last term on the right-hand-side. Let $B_{k,\ell'}>0$ be a solution to Equation 56 for any $t\in\mathcal{T}_{k,\ell'}$ or a "locally present pest." For any $t\notin\mathcal{T}_{k,\ell'}$, or "non-locally present pest," $B_{t,k,\ell',\ell'}=0$ as argued earlier. Thus, if we define $1-\delta_{k,\ell',\ell}=\frac{1}{T}|\mathcal{T}_{k,\ell}\cap\mathcal{T}_{k,\ell'}|$ as the fraction of overlapping CPPs, we can write

$$\frac{1-\alpha}{T}\sum_{\tau\in\mathcal{T}_{k,\ell}}\tau(\hat{B}_{t,k,\ell',\ell'})=(1-\alpha)(1-\delta_{k,\ell',\ell})\tau(B_{k,\ell'})+0\cdot\delta_{k,\ell',\ell}=(1-\alpha)(1-\delta_{k,\ell',\ell})\tau(B_{k,\ell'})\tag{59}$$

B.3 Model Predictions

We now review the predictions of this extended model, mirroring the analysis of Section 2.2.

The Uneven Focus of Innovation. The extended model features a richer set of mechanisms by which innovation is endogenously directed to the environmental characteristics of large markets. To see this, we first describe the profit incentives that shape the decisions of innovators based in any given *origin* market ℓ'. From the first-order condition (Equation 56), we observe that the marginal benefit from research investment is higher under the following circumstances: high baseline agricultural productivity ($\omega_{k,\ell}$), high markups ($q_{k,\ell',\ell} = C_\ell$), low licensing or IP costs ($\rho_{\ell',\ell}$), and low input-use wedges ($\zeta_{k,\ell}$) all increase the marginal return to R&D investment. Moreover, because of knowledge spillovers from research on local ecological characteristics—and *endogenous* mechanism that generates increasing returns to scale for research—agricultural R&D in a given country ℓ' is further directed toward destination markets with similar ecologies. Finally, because of the intensive margin of research investment, there is a further "multiplier" force captured by the coefficient $\frac{1}{1+\phi-\eta(1-\alpha)}$ in Equation 58: when input demand is more elastic to the environmental adaptations of technology (lower α or higher η), the innovator internalizes the fact that producing higher quality technology will raise agricultural productivity (and their market share), further increasing the demand for agricultural technology.

Next, fixing the destination market (k, ℓ), we observe that the productivity boost for technology ℓ' arising from knowledge spillovers scales with the extent of R&D specific to domestic ecological threats in those markets (Equation 59). The extent of this research is, in turn, affected by all the forces described above related to market size. Thus, research "leaders" endogenously emerge in the multi-country model. Fixing a crop k, the highest-quality technology comes from the market ℓ' which endogenously generates the most technology, due to its low R&D costs, high baseline productivity, and/or favorable IP environment. These are also the markets for which lower ecological mismatch has the highest marginal benefit.

Mismatch and Technology Diffusion. We next study the implications for technology diffusion. As in the proof of Proposition 1, we substitute the expression for the endogenous productivity of technology (Equation 58) into aggregate demand for agricultural technology and then collect terms. We obtain an expression of the form

$$\log X_{k,\ell',\ell} = -\beta_{k,\ell'}\delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell',\ell'} + \varepsilon_{k,\ell',\ell} \tag{60}$$

This is a multi-way fixed effects equation that exactly matches our empirical strategy described in Section 5.1.

The coefficient on ecological mismatch is

$$\beta_{k,\ell'} = \frac{\eta(1-\alpha)\tau(B_{k,\ell'})}{1+\phi-\eta(1-\alpha)} \geq 0 \tag{61}$$

This coefficient depends on the crop and origin market through the extent of knowledge spillover.

In particular, the model predicts that mismatch has a larger marginal effect (in absolute value) on technology transfer when the origin market is more research-intensive. This prediction is consistent with our findings in Section 5.3.

We next describe interpretations of the fixed effect variables χ.[25] The "crop-by-destination" fixed effect partials out the effects of destination market size and destination-specific input-market wedges, forces that have a uniform effect on technology transfer from any origin country:

$$\begin{aligned}\chi_{k,\ell} = &\left(\frac{(1-\alpha)\eta}{1+\phi-\eta(1-\alpha)}+\eta\right)\log\omega_{k,\ell}+(1-\eta)\left(\frac{1-\alpha}{1+\phi-\eta(1-\alpha)}+1\right)\log\Xi_\ell \\ &+-\eta\frac{1+\gamma}{\gamma}\log C_\ell+\frac{\eta(1-\alpha)}{1+\phi-\eta(1+\alpha)}\log K_1(C_\ell)-\frac{\eta(1-\alpha)}{1+\phi-\eta(1+\alpha)}\log\tilde{\zeta}_{k,\ell} \\ &+\frac{1-\alpha}{1+\phi-\eta(1-\alpha)}+\frac{1-\alpha}{1+\phi-\eta(1-\alpha)}\log\big(K_0(\gamma,\eta)\eta(1-\alpha)\big)+\log K_0(\gamma,\eta)\end{aligned} \tag{62}$$

The "crop-by-origin" fixed effect partials out the research productivity of the origin country, which has a uniform effect on all destination countries:

$$\chi_{k,\ell'} = \frac{\eta\alpha(1+\phi)^{-1}}{1+\phi-\eta(1-\alpha)}\log A_{k,\ell'}+\frac{\eta(1-\alpha)\tau(B_{k,\ell'})}{1+\phi-\eta(1-\alpha)}-\frac{(1-\alpha)(1+\phi)^{-1}}{1+\phi-\eta(1-\alpha)}\log B_{0,\ell'} \tag{63}$$

The "origin-by-destination" fixed effect partials out the direct effect of bilateral trade and licensing costs:

$$\chi_{\ell,\ell'} = -\frac{\eta(1-\alpha)}{1+\phi-\eta(1-\alpha)}\rho_{\ell,\ell'} \tag{64}$$

Finally, the structural residual captures idiosyncratic factors in the country ℓ' innovator's expectations of demand in market (k,ℓ):

$$\varepsilon_{k,\ell',\ell} = \frac{\eta(1-\alpha}{1+\phi-\eta(1-\alpha)}\log\xi_{k,\ell',\ell} \tag{65}$$

In principle, when estimating Equation 61, a threat to identifying the coefficient of interest β is spurious correlation between ecological mismatch and this residual shock to expectations. In Section 5.1, we describe empirical strategies that allay this concern in practice.

Mismatch and Agricultural Production. We next study the extended model's predictions for mismatch and agricultural production. Because of the structure of the choice problem with Fréchet valued shocks, there is a simple mapping to the model studied in Section 2. We define the crop-specific productivity index

$$\theta_{k,\ell} = \left(\sum_{\ell'}\theta^{\eta}_{k,\ell',\ell}\right)^{\frac{1}{\eta}} \tag{66}$$

[25] As in the proof of Proposition 1, we observe that the fixed effect decomposition is not unique.

This index summarizes farmers' choice over technology ℓ'. In particular, we can write the total fraction of farmers planting crop k in country ℓ by combining this definition with Equation 52:[26]

$$\pi_{k,\ell} = \sum_{\ell'} \pi_{k,\ell',\ell} = \frac{p_k^{\frac{\eta}{\gamma}} \zeta_{k,\ell}^{-\eta\frac{1-\gamma}{\gamma}} \omega_{k,\ell}^{\eta}}{\sum_{k'} p_{k'}^{\frac{\eta}{\gamma}} \zeta_{k',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \omega_{k',\ell}^{\eta}} \tag{67}$$

Using this observation, we can write production of crop k in country ℓ (cf. Proposition 2) as

$$\log Y_{k,\ell} = \eta \cdot \log \theta_{k,\ell} + \chi_k + \chi_\ell + \nu_{k,\ell} \tag{68}$$

Our estimating equation can be understood as an approximation of this model when a small number of leaders have most of the market share for inputs. The fixed effects are defined as in Proposition 2:

$$\begin{aligned} \chi_k &= \left(\frac{\eta}{\gamma} - 1\right) \log p_k \\ \chi_\ell &= (1-\eta) \log \Xi_\ell + \eta \frac{1-\gamma}{\gamma} (\log(1-\gamma) - \log C_\ell) \end{aligned} \tag{69}$$

The structural residual now takes into account both local productivity and local input-use wedges:

$$\nu_{k,\ell} = \eta \log \omega_{k,\ell} - \frac{\eta(1-\gamma)}{\gamma} \log \zeta_{k,\ell} \tag{70}$$

Note that only *country-by-crop specific* components of the wedge are relevant for identification; any country-specific or crop-specific components would be flexibly controlled for by the relevant fixed effects. In practice, we find that our estimates of the effect of mismatch on production are stable when controlling for observable proxies of innate productivity as well as proxies for wedges constructed by interacting crop fixed effects with measures of overall development and human capital.

Inappropriate Technology and Productivity. We finally observe that revenue productivity is defined above in Equation 53. Revenue productivity is lower when agricultural technology is less productive, and its exact form in the model encodes farmers' ability to substitute across crops and technology types. In the extended model, innate productivity also accounts for market-specific wedges. Since our structural analysis recovers innate productivity as a residual to account for observed production (see Section 7.1), our method can be understood as holding these wedges constant.

[26]We also use the fact that input prices are constant at the country level, and therefore irrelevant for choice across crops or technologies within country.

C. Inappropriateness Driven By Agro-Climatic Conditions

This appendix investigates the possible importance of non-CPP agro-climatic conditions as shifters of ecological inappropriateness. We estimate ecological differences across crop-specific growing areas in different countries, and incorporate these additional measures of mismatch into both our baseline empirical estimates and counterfactual results.

C.1 Constructing Agro-climatic Mismatch

We include ten key agro-climatic characteristics that shape the usefulness of biotechnology for production in a region: temperature, precipitation, elevation, ruggedness, the length of the growing season, soil acidity, soil clay content, soil silt content, soil coarse fragment content, and soil water capacity.[27] We combine geographically coded raster files of each characteristic with grid-cell level information from the EarthStat database on the global planting pattern of 175 important crops in 2000 (Monfreda et al., 2008).[28] We then compute the value of each characteristic for each crop-by-country pair by estimating the average value of each characteristic in each country on the land devoted to the crop in question; we denote these as $x_{k,\ell}$. We then normalize each characteristic to comparable, z-score units by re-centering by the global mean value of each attribute and normalizing by the global dispersion (standard deviation); we refer to these normalized values as $\hat{x}_{k,\ell}$. Then, for each agro-climatic characteristic x, crop, and location pair, we define the absolute distances

$$\Delta\hat{x}_{k,\ell,\ell'} = |\hat{x}_{k,\ell} - \hat{x}_{k,\ell'}| \tag{71}$$

In words, $\Delta\hat{x}_{k,\ell,\ell'}$ is the normalized mismatch ("inappropriateness") in agro-climatic feature x for crop k between countries ℓ and ℓ'. For simplicity, we also aggregate the individual agroclimatic characteristics into a single index at the crop-by-country-pair level, summing over all characteristics $\mathcal{X}$:[29]

$$\text{AgroClimMismatch}_{k,\ell,\ell'} = \frac{1}{|\mathcal{X}|} \cdot \sum_{x\in\mathcal{X}} \Delta\hat{x}_{k,\ell,\ell'} \tag{72}$$

C.2 Empirical Estimates

We next investigate whether mismatch in agro-climatic features shapes the transfer of technology and global patterns of production. In column 1 of Table A8 reports estimates of Equation 9 in which, instead of CPP mismatch, we include all ten agro-climatic mismatch measures $\Delta x_{k,\ell,\ell'}$ on the right hand side of the regression. We find that most are negative and several statistically significant. Mismatch in temperature, precipitation, and soil pH are associated with the largest reductions in technology transfer. In column 2, we include the one-dimensional $\text{AgroClimMismatch}_{k,\ell,\ell'}$ instead

[27] The temperature and precipitation data from National Center for Atmospheric Research Staff (Eds) (2020); elevation from the GTOP30 Digital Elevation model; ruggedness from Riley et al. (1999) via Nunn and Puga (2012); growing season length from FAO GAEZ; and soil statistics from WoSIS (Batjes et al., 2020, `https://www.isric.org/explore/wosis`).

[28] The data set was created by combining national, state, and county level census data with crop-specific maximum potential yield data, to construct a 5-by-5-minute grid of the area devoted to each crop circa 2000.

[29] The index is similar to the agro-climatic similarity index used by Bazzi et al. (2016).

of the individual $\Delta x_{k,\ell,\ell'}$. The coefficient on agro-climatic mismatch is negative and significant. Columns 3 and 4 repeat the estimates from columns 1 and 2, except we also include CPP mismatch on the right hand side of the regression. The effect of CPP mismatch is negative, significant, and similar to our baseline estimate, suggesting that ecological mismatch due to CPPs and due to other agro-climatic features operate largely independently.

In Figure A6c, we present our results for production. The dependent variable is log of agricultural output and the regression specification is (11). Again, we find a large, negative effect of agro-climatic mismatch on production, suggesting that this independently measured form of ecological mismatch affects agricultural output. Again, this operates largely independently from CPP mismatch, which remains negative and significant ($\beta = -5.92$ $t = 4.98$) once agro-climatic mismatch is included in the regression.

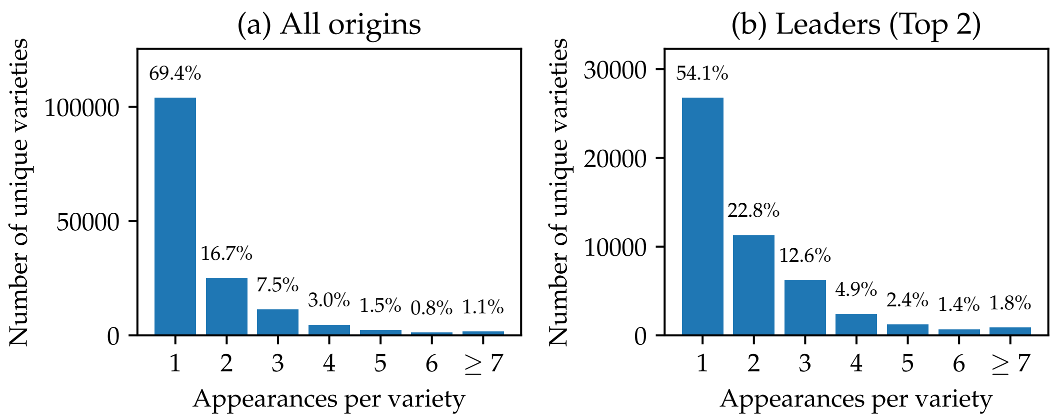
Taken together, these results show that our main findings are not specific to CPP differences across crops and places (or, more perniciously, not driven by some specific feature of our CPP data and measurement strategy); other agro-climatic shifters of inappropriateness also affect technology transfer and productivity gaps. At the same time, non-CPP agro-climatic differences seem to operate independently from our baseline measure of CPP mismatch, suggesting that the baseline estimates are not simply picking up standard features of climate and geography. These findings are all consistent with the fact that the pairwise correlations between CPP mismatch with the frontier, and mismatch with the frontier in each other ecological characteristic, is relatively low. Table A1 reports a correlation matrix, including CPP distance to the frontier along with all agro-climatic characteristics discussed above. The first column shows the correlation between CPP distance and all other distance measures; the correlation coefficients tend to be small, and only one is above 0.2.

C.3 Counterfactual Analysis

Finally, we estimate our baseline counterfactuals scenario incorporating both CPP mismatch and acro-climatic mismatch. Our modeling strategy is identical to the one outlined in Section 7.1 of the main text. We find that inappropriateness, as captured by both CPP mismatch and agro-climatic mismatch, reduces global productivity by 68.2% and increases disparities in global productivity across countries, measured by the interquartile range, by 16.3%. These results are summarized graphically in Figure A12, which is structured in the same way as Figure 10. Incorporating agro-climatic mismatch as an additional shifter of inappropriateness increases our estimate of the overall effect of inappropriateness on productivity. However, the effect of CPP mismatch on global output is about four times as large as the effect of agro-climatic mismatch, suggesting that inappropriateness in the form of CPP mismatch is a more important determinant of agricultural productivity.

D. Supplementary Figures and Tables

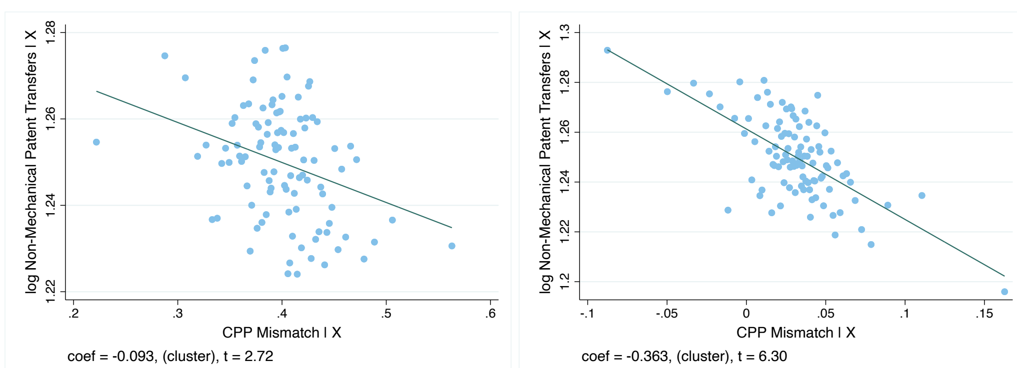
Figure A1: The Diffusion of Crop Varieties in the UPOV Data



Notes: Each plot is a histogram of the number of appearances per unique variety in our data on new variety introduction from the International Union for the Protection of New Varieties of Plants (UPOV). Our method for defining technology transfer is described in Section 3.2.1. Panel (a) is for the whole sample. Panel (b) is for varieties from crop-specific "leaders," defined as the two countries that are associated with the most variety registrations for that crop (Section 5.3).

Figure A2: The Effect of CPP Mismatch on the Transfer of Biological and Chemical Technologies

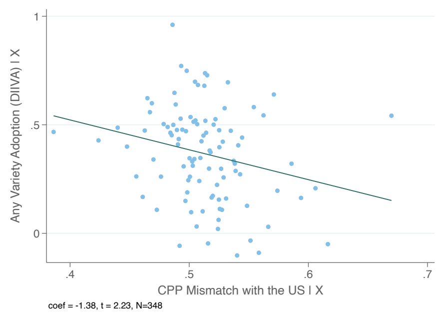
(a) Non-Mechanical Technology **(b)** Non-Mechanical Technology (Leader Effect)



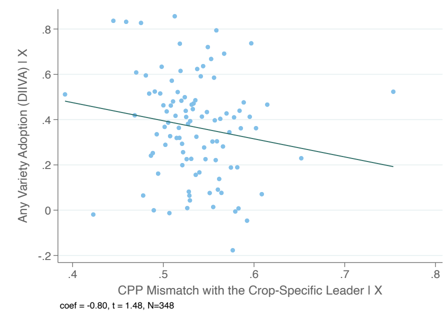
Notes: Each sub-figure reports a binned partial correlation plot (in which all possible two-way fixed effects are absorbed) corresponding to the effect of crop pest and pathogen (CPP) mismatch on the transfer of biological and chemical technologies. The outcome variable is defined by the international transfer of agricultural patents (those in CPC class A01; see Section 3.2.2) *outside* of classes A01B, A01C, or A01D. Panel (a) reports the average effect of CPP mismatch (estimated from Equation 9) and (b) reports the effect of CPP mismatch with the leader (estimated from Equation 10).

Figure A3: The Effect of CPP Mismatch on Variety Transfer to sub-Saharan Africa

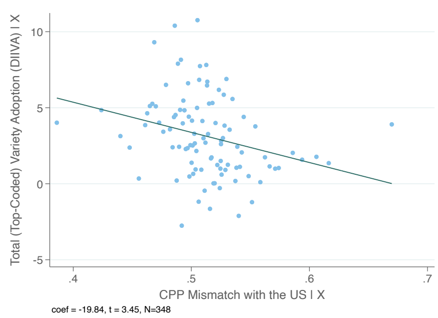
(a) Mismatch with the US (Extensive Margin)



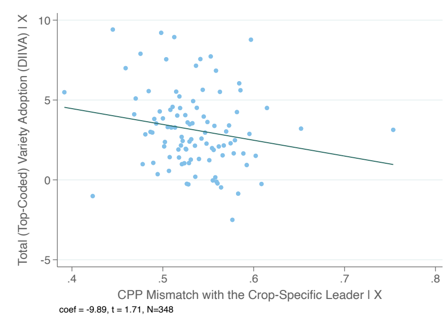
(b) Mismatch with Estimated Leader (Extensive Margin)



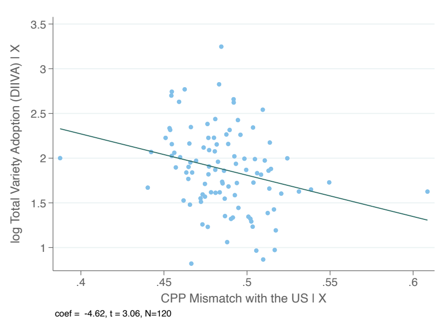
(c) Mismatch with the US (Top-Coded)



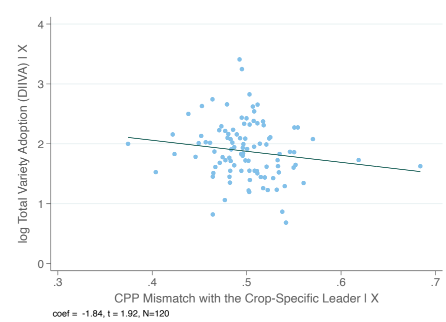
(d) Mismatch with Estimated Leader (Top-Coded)



(e) Mismatch with the US (log Count)



(f) Mismatch with Estimated Leader (log Count)



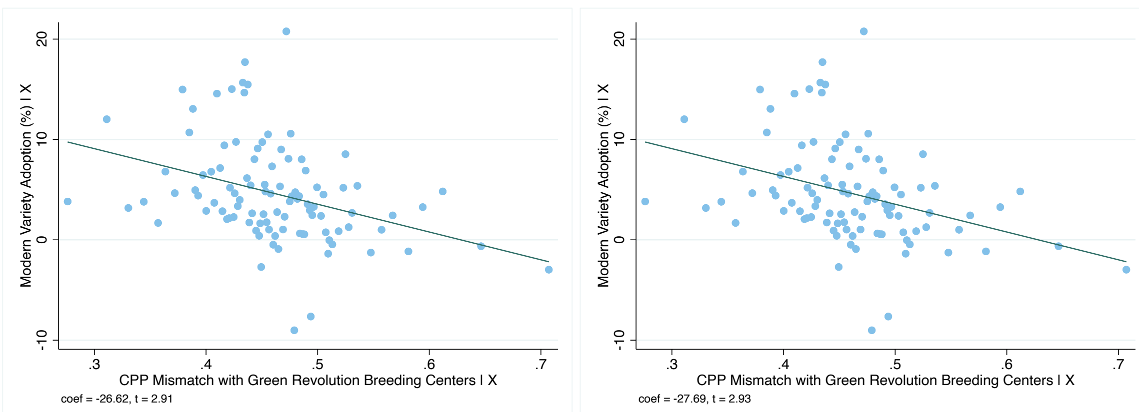
Notes: This figure displays binned partial correlation plots, after absorbing country and crop fixed effects, of the following regression equation at the level of crops k and countries ℓ:

$$y_{k,\ell} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell} + \chi_\ell + \chi_k + \varepsilon_{k,\ell}$$

Our outcome data come from the CGIAR DIIVA project (see Section 5.5), covering 19 crops and 28 countries in sub-Saharan Africa. In the left panel, we measure CPPMismatchFrontier using mismatch with the United States. In the right panel, we use CPP mismatch with (two) crop-specific leaders identified in the UPOV data, as described in Section 6.1. In (a) and (b), the outcome is an indicator that equals one if any adoption has taken place; in (c) and (d), it is the total number of varieties adopted (top-coded at the 95th percentile); and in (e) and (f), it is the log of the total number of varieties adopted. We report t-statistics based on robust standard errors.

Figure A4: The Effect of CPP Mismatch on the Diffusion of High-Yield Varieties of the Green Revolution

(a) Baseline Specification | **(b)** Crop-by-Continent Fixed Effects



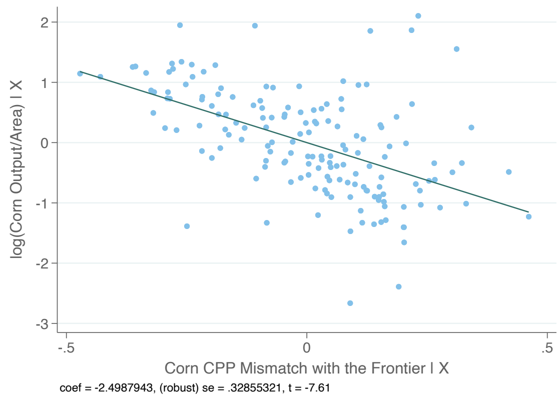
Notes: Each sub-figure reports a binned partial correlation plot of the relationship between Green Revolution variety adoption and CPP mismatch with the Green Revolution, both measured at the crop-by-country level. We estimate the regression equation,

$$\text{HYVAdoption}_{k,\ell,1985} = \beta \cdot \text{CPPMismatchGR}_{k,\ell} + \chi_{\ell} + \chi_{k,c(\ell)} + \varepsilon_{k,\ell}$$

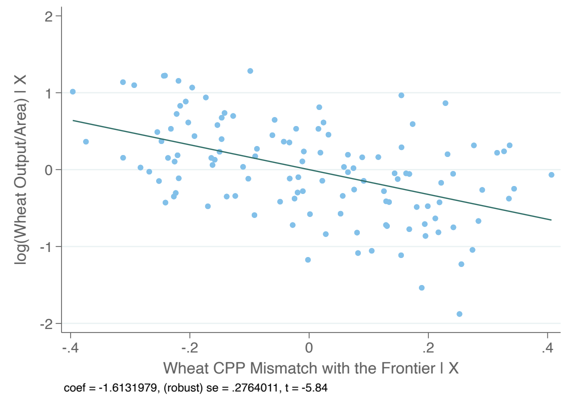
The outcome is measured from Evenson and Gollin's (2003) data on high-yield variety adoption. CPPMismatchGR is calculated as the crop-specific mismatch with the relevant international agricultural research center (IARCs) identified in Table A14. In (a), both crop and country fixed effects are included in the regression and in (b), crop fixed effects are replaced with crop-by-continent fixed effects. Standard errors are double-clustered by country and crop-continent pair.

Figure A5: The Effect of CPP Mismatch on Agricultural Yields

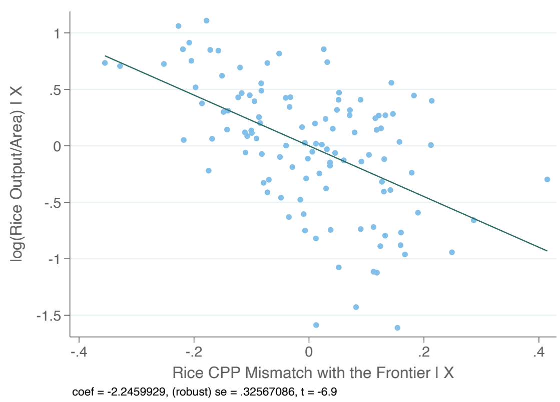
(a) Corn



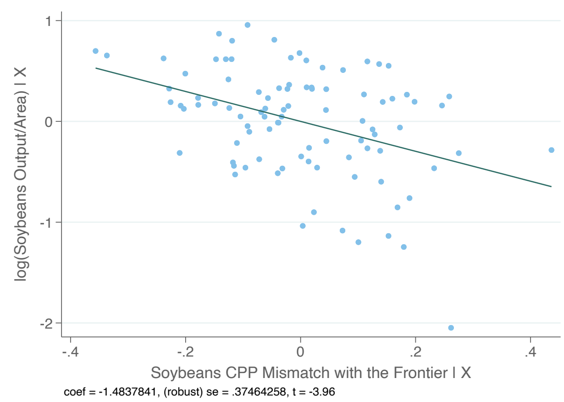
(b) Wheat



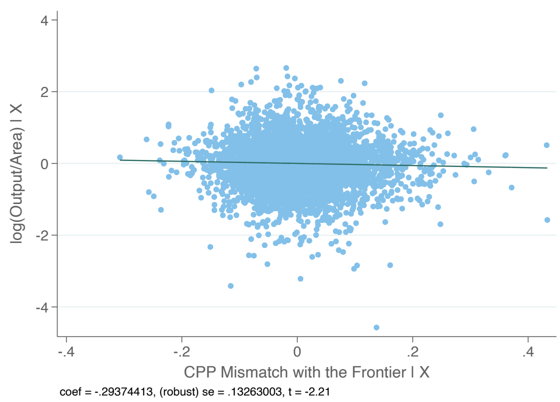
(c) Rice



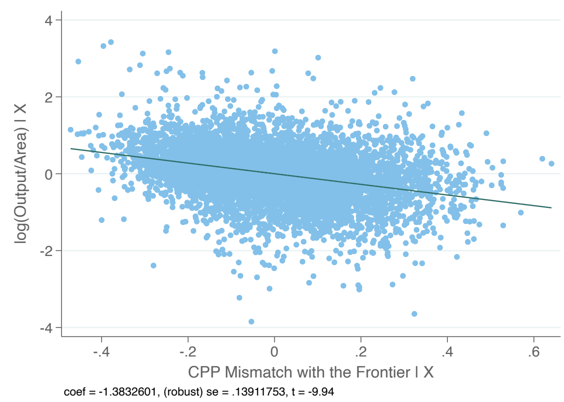
(d) Soybeans



(e) All Crops



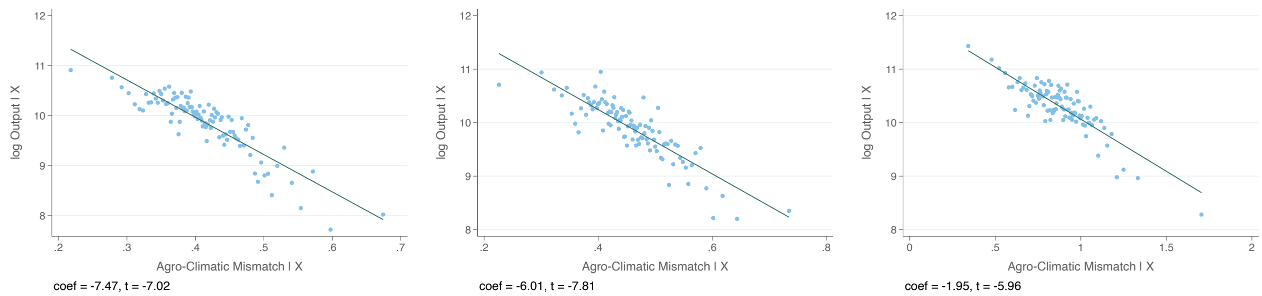
(f) All Crops (No Country FE)



Notes: Each sub-figure reports a partial correlation plot of a different estimation of Equation 11. In A5a - A5d, we restrict the sample to corn, wheat, rice, and soybeans respectively. In A5e and A5f, the sample includes all crops and in A5f country fixed effects are removed from the regression equation. The dependent variable is log of output per acre. The coefficient estimates and standard errors are noted at the bottom of each sub-figure.

Figure A6: The Effect of CPP Mismatch on Output: Measurement Sensitivity

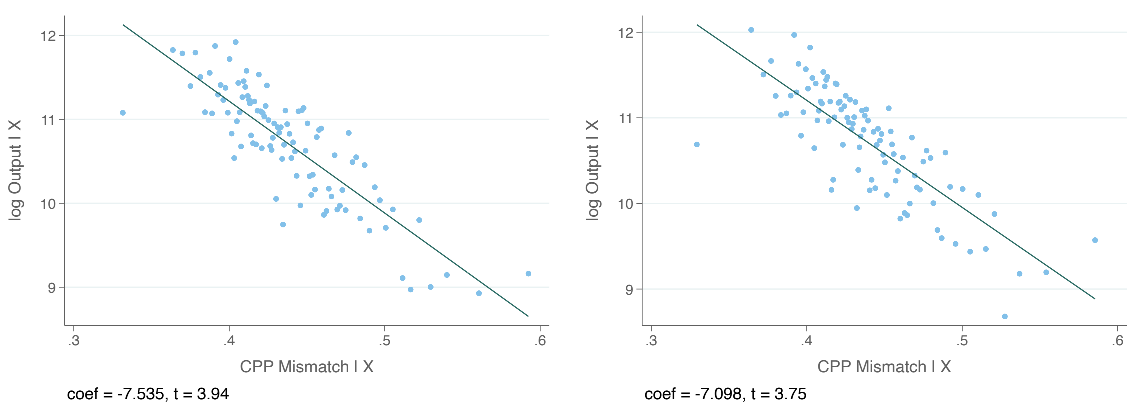
(a) Including Eradicated CPPs **(b)** Excluding Invasive CPPs **(c)** Agro-Climatic Mismatch



Notes: Each sub-figure reports a binned partial correlation plot of the relationship between log of crop-specific output and ecological mismatch with the crop-specific leader country. In (a), we measure CPP mismatch after including all CPPs that have ever been eradicated according to the CABI CPC data. In (b), we measure CPP mismatch after excluding all CPPs that have ever been invasive or that have high invasive potential according to the CABI Invasive Species Compendium. In (c), we measure agro-climatic mismatch using features of geography and the climate, as described in Appendix C. Crop and country fixed effects are included in all specifications. Standard errors are double-clustered by country and crop-continent pair.

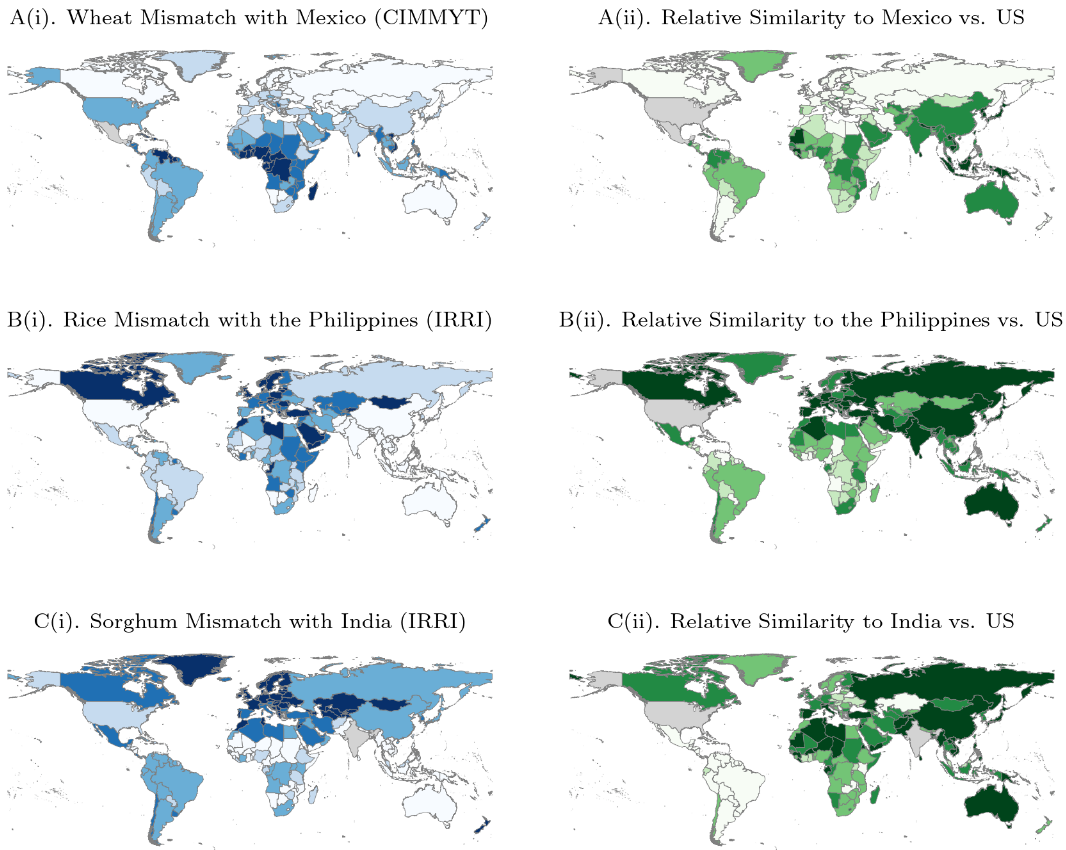
Figure A7: The Effect of CPP Mismatch and Output After Controlling for Potential Market Expansion

(a) Rain-Fed Model **(b)** Irrigated Model



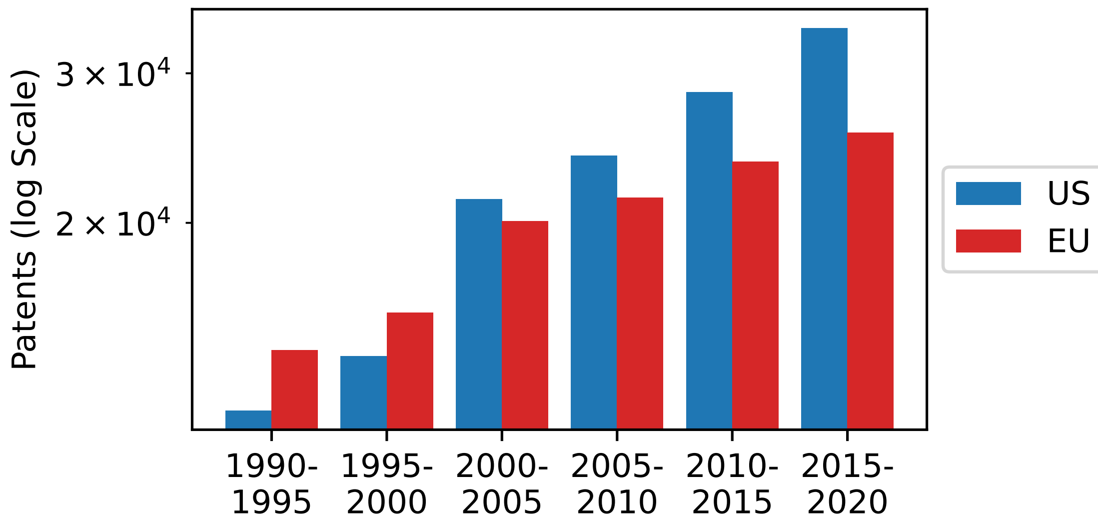
Notes: Each sub-figure reports a binned partial correlation plot of the relationship between log of crop-specific output and CPP mismatch with the crop-specific leader country, controlling for crop and country fixed effects as well as a proxy for potential market expansion from improved agricultural technology. Following Bustos et al. (2016), we construct proxies for potential expansion using the difference between the (log of) potential output predicted by the high-input and low-input versions of the FAO-GAEZ agro-ecological model. In panel (a), we construct the control using the variant of the FAO-GAEZ model that assumes rain-fed agriculture in both high-input and low-input settings. In panel (b), we use the variant of the model that assumes the use of irrigation in high-input settings. Standard errors are double-clustered by country and crop-continent pair.

Figure A8: Illustrating the Variation in CPP Mismatch for the Green Revolution



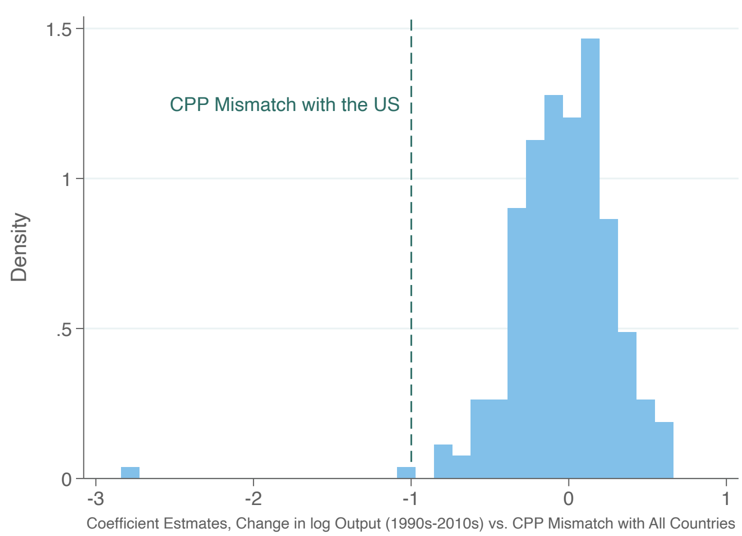
Notes: These maps illustrate the variation in CPP (crop pest and pathogen) mismatch with centers of Green Revolution breeding. The three rows correspond to wheat, based in the Centro Internacional de Mejoramiento de Maíz y Trigo (CIMMYT) in Mexico; rice, based in the International Rice Research Institute (IRRI) in the Phillipines; and sorghum, based in International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in India. Each map in the left column shows the distribution of CPP $\text{MismatchGR}_{k,\ell,\ell'}$ across countries ℓ' fixing the indicated crop k and demeaned at the destination ℓ' and crop k levels. Darker shades of blue indicate higher values (i.e., more different crop pest and pathogen environments), coded into five quantiles. Each map in the right column shows the difference betweeen CPP Mismatch with the United States and CPP Mismatch with the relevant Green Revolution breeding center, demeaned in the same way. Darker shades of green denotes higher relative mismatch with the US or higher relative similarity with the Green Revolution center, coded into five quintiles.

Figure A9: Growth in Patented Agricultural Technologies, Europe vs. the United States



Notes: This graph shows the total number of patented agricultural technologies (i.e., in CPC class A01) in each five year period, comparing patents with assignees in the US to patents with assignees in the modern EU (as of 2018). Bars are the number of patents issued in the five year bin noted on the horizontal axis.

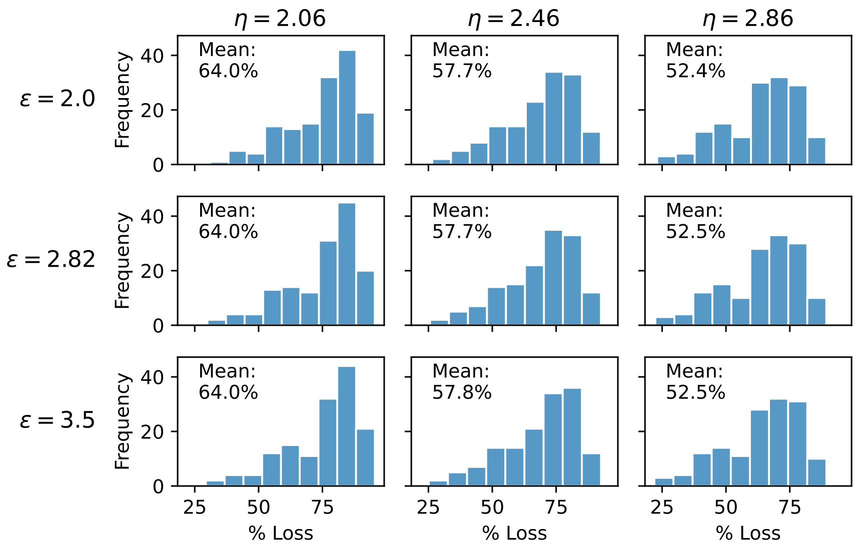
Figure A10: Falsification Test: CPP Mismatch with All Countries and Output Growth (1990s-2010s)



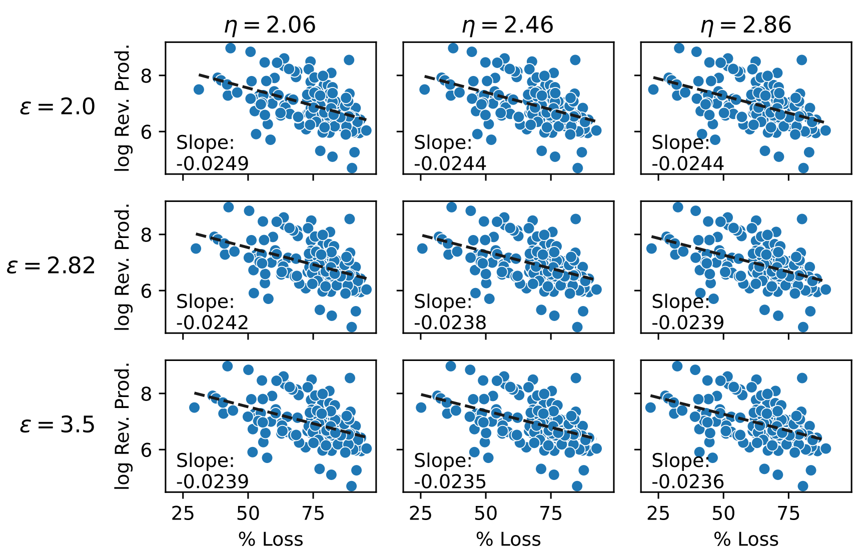
Notes: This figure displays histograms of the coefficient estimates of the relationship between CPP mismatch with each country separately and log of crop-level output change between the 1990s and the 2010s, as a randomization tset of our estimates of Equation 15. The effect of CPP mismatch with the US is marked with a dotted line. The implied p-values from this permutation test is $p = 0.004$.

Figure A11: Sensitivity Analysis of Counterfactual Experiment

(a) Losses by Country

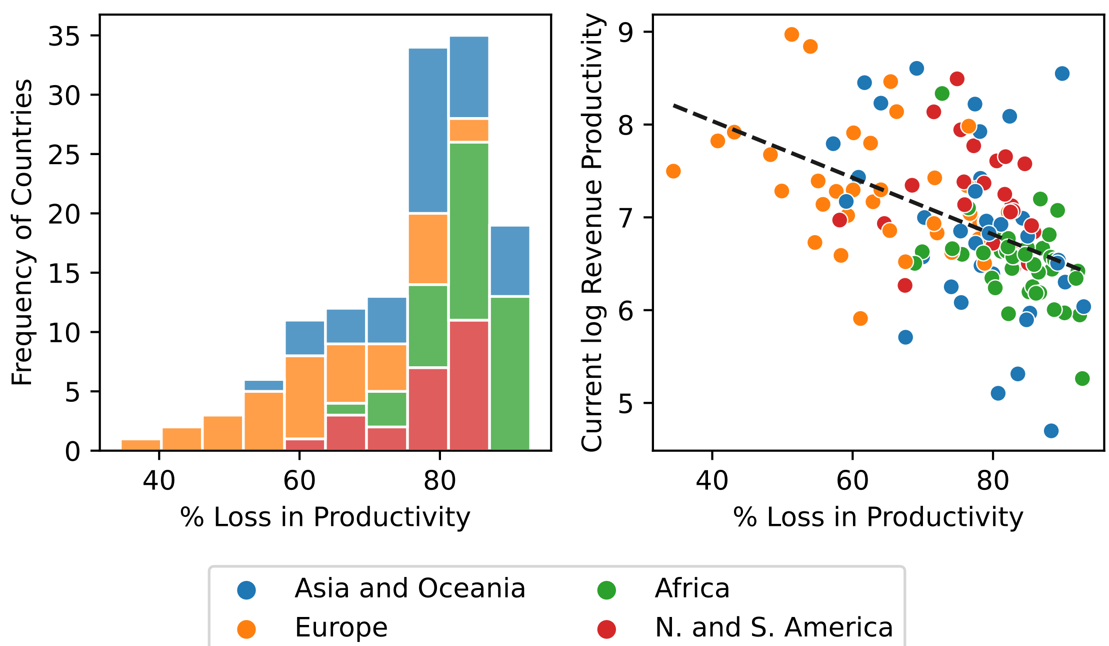


(b) Losses vs. Observed Productivity



Notes: This figure reproduces the main findings of our counterfactual exercise of removing inappropriateness under alternative values of the inverse elasticity of supply η and elasticity of demand ε. For the maximum and minimum plausible values for ε, we use $\varepsilon = 2$ and $\varepsilon = 3.5$. For the minimum plausible value for η, we use $\eta = 2.06$ from Sotelo (2020), to our knowledge the lowest estimate of the relevant parameter in existing literature. For the maximum plausible value, we add the difference between the Sotelo (2020) estimate and our baseline estimate of η.

Figure A12: The Effects of Inappropriateness on Global Agricultural Productivity, Incorporating Both CPP and Agro-Climatic Mismatch



Notes: This figure recreates Figure 10 under an experiment that removes inappropriateness due to both CPP mismatch and Agro-Climatic mismatch. Agro-climatic mismatch is a measure of the dissimilarity of ten features of climate, soil, and topography at the country-by-crop level, as described in Appendix C. The left graph is a histogram of productivity losses from inappropriateness across countries. The right graph is a scatterplot of productivity losses against observed productivity. The line is a best-fit linear regression across countries (slope = −0.031, robust SE = 0.005). In each plot, colors indicate continents.

Table A1: Correlations Between All Ecological Mismatch Measures

Difference in:	CPPs	Temp.	Precip.	Elevation	Rugged.	Soil Clay Content	Soil Silt Content	Coarse Frag. Content	Soil pH	Growing Season Length	Available Water Capacity
CPPs	1.0000										
Temp.	0.2356	1.0000									
Precip.	0.1061	0.2121	1.0000								
Elevation	0.1578	0.0104	-0.0405	1.0000							
Rugged.	0.1726	-0.0382	0.05	0.5052	1.0000						
Soil Clay Content	0.0374	0.1602	0.146	-0.0074	-0.0096	1.0000					
Soil Silt Content	0.1807	0.3564	0.0236	0.0402	-0.1209	0.0966	1.0000				
Soil Coarse Fragement Content	0.1045	0.0697	0.0188	0.3407	0.5595	-0.0999	-0.1013	1.0000			
Soil pH	0.0793	0.0829	0.4994	-0.0082	0.0128	0.1087	0.0326	-0.0001	1.0000		
Growing Season Length	0.084	0.1186	0.5092	-0.0121	0.009	0.0216	0.0275	0.0001	0.4116	1.0000	
Available Water Capacity	0.1375	0.1829	0.099	0.0126	-0.0466	0.3531	0.3893	-0.0966	0.0906	0.0665	1.0000

Notes: This table presents a correlation matrix among all individual measures of ecological distance to the frontier including CPP distance to the frontier. The additional characteristics are: temperature, precipitation, elevation, ruggedness, soil clay content, soil silt content, soil coarse fragement content, soil pH, growing season length, and available water capacity. Each cell reports a pairwise correlation coefficient.

Table A2: The Direction of Innovation Across Crops

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Technology Development (0/1)				log Technology Development			
log domestic crop production value	0.0581	0.0485	0.0449	0.0581	0.402	0.308	0.281	0.402
	(0.00584)	(0.00742)	(0.00697)	(0.00584)	(0.0321)	(0.0339)	(0.0307)	(0.0321)
log global crop production value		0.0234	-0.00569			0.218	-0.00987	
		(0.00811)	(0.0140)			(0.0277)	(0.0694)	
log IP weighted global crop production value			0.0401				0.202	
			(0.0258)				(0.0987)	
log GDP weighted global crop production value			-0.00667				0.0612	
			(0.0273)				(0.112)	
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	No	No	No	Yes	No	No	No	Yes
Observations	2,245	2,245	2,243	2,245	1,420	1,420	1,419	1,420
R-squared	0.430	0.434	0.438	0.430	0.462	0.489	0.502	0.462

Notes: The unit of observation is a country-crop pair. In columns 1-4, the outcome variable is an indicator that equals one if there is variety development related to the crop in the country, and in columns 5-8, it is the log number of varieties released related to the crop in the country. Variety development is measured using the UPOV PLUTO data. Country fixed effects are included in all specifications and crop fixed effects are included in columns 4 and 8. Standard errors are clustered by country.

Table A3: CPP Mismatch and Technology Transfer: Private vs. Non-Private Innovation

	(1)	(2)	(3)
	Dependent Variable is Any Transfer (0/1)		
	All	Private Sector	Public Sector or University
	Panel A: Crop Variety Transfers		
CPP Mismatch (0-1)	-0.0275	-0.0229	-0.0101
	(0.0106)	(0.0097)	(0.0032)
Dependent Variable Mean	0.0429	0.0384	0.0123
Observations	204,287	204,287	204,287
R-squared	0.3829	0.3800	0.1753
	Panel B: Patented Technology Transfers		
CPP Mismatch (0-1)	-0.0072	-0.0066	-0.0030
	(0.0017)	(0.0017)	(0.0009)
Dependent Variable Mean	0.0142	0.0133	0.0037
Observations	5,661,392	5,661,392	5,661,392
R-squared	0.6254	0.6251	0.4680
	Panel C: Patented Technology Citations		
CPP Mismatch (0-1)	-0.0015	-0.0014	-0.0005
	(0.0006)	(0.0005)	(0.0003)
Dependent Variable Mean	0.0020	0.0019	0.0006
Observations	5,661,392	5,661,392	5,661,392
R-squared	0.5167	0.5170	0.3892
Crop-by-Origin Fixed Effects	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes
Origin-by-Destination Fixed Effects	Yes	Yes	Yes

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. In Panel A, the outcome variable is constructed using variety transfer data from the UPOV database; in Panel B, it is constructed from patent tranfer data using patent family information; and in Panel C, it is constructed from patent citation data using the full citation network of all patented agricultural technologies. CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. The outcome variable is an indicator that equals one if any technology transfer has taken place. Columns 2 and 3 restrict the outcome to technologies developed by the privatea sector or by the public sector/university researchers, respectively. Standard errors are double-clustered by origin and destination.

Table A4: CPP Mismatch with Leader Countries and Technology Transfer: Intensive Margin

Leader defined as:	(1) United States	(2) Top Variety Developer	(3) Top 2 Variety Developers	(4) Top 3 Variety Developers
	Panel A: Dependent Variable is Total Transfers (Top-Coded)			
CPP Mismatch (0-1)	-0.3023	-0.1806	-0.1016	-0.0235
	(0.1109)	(0.1058)	(0.0981)	(0.1070)
CPP Mismatch (0-1) x Leader (0/1)	-0.9285	-9.7274	-7.8068	-6.7234
	(0.1769)	(2.8657)	(2.2666)	(1.9940)
Observations	204,287	204,287	204,287	204,287
R-squared	0.3400	0.3448	0.3457	0.3460
	Panel B: Dependent Variaablee is log Transfers			
CPP Mismatch (0-1)	-1.1607	-1.0844	-1.1542	-0.8521
	(0.3643)	(0.3500)	(0.3223)	(0.3811)
CPP Mismatch (0-1) x Leader (0/1)	-0.6976	-0.6938	-0.1727	-0.8920
	(1.2475)	(0.4234)	(0.5030)	(0.4366)
Observations	5,791	5,791	5,791	5,791
R-squared	0.7967	0.7968	0.7967	0.7972
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	Yes
Country Pair Fixed Effects	Yes	Yes	Yes	Yes

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. The outcome variable is the total number of variety transfers, top-coded at the 95th percentile (Panel A) or the log of the total number of variety transfers (Panel B). CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. Each regression also includes an interaction between CPP mismatch and an indicator that equals one if the origin is a leader country, for different definitions of the leader country (noted at the top of each column). Standard errors are double-clustered by origin and destination.

Table A5: CPP Mismatch with Leader Countries and Technology Transfer: Patent Transfer and Citations

	(1)	(2)	(3)	(4)
	Dependent Variable is Any Technology Transfer (0/1)			
Leader defined as:	United States	Top Variety Developer	Top 2 Variety Developers	Top 3 Variety Developers
	Panel A: Patented Technology Transfers			
CPP Mismatch (0-1)	-0.0069	-0.0068	-0.0066	-0.0064
	(0.0017)	(0.0017)	(0.0016)	(0.0016)
CPP Mismatch (0-1) x Leader (0/1)	-0.0697	-0.1376	-0.1153	-0.1059
	(0.0029)	(0.0275)	(0.0202)	(0.0231)
Observations	5,661,392	5,661,392	5,661,392	5,661,392
R-squared	0.6254	0.6256	0.6257	0.6258
	Panel B: Patented Technology Citations			
CPP Mismatch (0-1)	-0.0015	-0.0014	-0.0013	-0.0013
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
CPP Mismatch (0-1) x Leader (0/1)	-0.0121	-0.0387	-0.0303	-0.0321
	(0.0010)	(0.0111)	(0.0097)	(0.0099)
Observations	5,661,392	5,661,392	5,661,392	5,661,392
R-squared	0.5167	0.5168	0.5168	0.5169
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	Yes
Country Pair Fixed Effects	Yes	Yes	Yes	Yes

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. The outcome variable is an indicator that equals one if any patent transfer has taken place (Panel A) or any patent citation has taken place (Panel B). CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. Each regression also includes an interaction between CPP mismatch and an indicator that equals one if the origin is a leader country, for different definitions of the leader country (noted at the top of each column). Standard errors are double-clustered by origin and destination.

Table A6: CPP Mismatch Inhibits International Technology Transfer: Crop Heterogeneity

	(1)	(2)	(3)
Crop characteristic:	Staple Crop Indicator	GMO Indicator	High Innovation Indicator
	Panel A: Crop Variety Indicator		
CPP Mismatch (0-1) x Crop Characteristic	-0.4347	-0.2804	-0.3927
	(0.0694)	(0.0489)	(0.0605)
Observations	204,287	204,287	204,287
R-squared	0.3855	0.3842	0.3858
	Panel B: Total Variety Transfers (Top-Coded)		
CPP Mismatch (0-1)	-5.9619	-4.5984	-6.0030
	(1.4104)	(1.1968)	(1.4146)
Observations	204,287	204,287	204,287
R-squared	0.3426	0.3418	0.3436
	Panel C: Log Variety Transfers		
CPP Mismatch (0-1)	-3.8514	-2.7842	-2.9533
	(0.7159)	(0.6502)	(0.6551)
Observations	5,791	5,791	5,791
R-squared	0.7993	0.7982	0.7986
Crop-by-Origin Fixed Effects	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes
Origin-by-Destination Fixed Effects	Yes	Yes	Yes

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. In Panel A, the outcome is an indicator for any variety transfer; in Panel B, it is the total number of variety transfers, top-coded at the 95th percentile; and in Panel C, it is the log of total variety transfers. CPP mismatch is constructed at the crop-country-pair level as the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. Each panel reports the coefficient on an interaction between CPP mismatch and the crop-level indicator listed at the top of the column. "High Innovation" means that the crop is in the top 10% of total global variety releases. Standard errors are double-clustered by origin and destination.

Table A7: CPP Mismatch Inhibits International Technology Transfer: Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Any Variety Transfer						
CPP Mismatch (0-1)	-0.0275	-0.0373	-0.0311	-0.0226	-0.0289	-0.0204	-0.0239
	(0.0106)	(0.0119)	(0.0098)	(0.0100)	(0.0113)	(0.0085)	(0.0082)
CPP Mismatch Including Eradications		✓					
CPP Mismatch Excluding Invasive Species			✓				
Control for bilateral crop-level trade				✓			
Control for log bilaterial distance x Crop FE					✓		
Exclude country pairs <1000km apart						✓	
Exclude country pairs <2000km apart							✓
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Pair Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204,287	204,345	202,258	204,287	189,302	185,344	156,007
R-squared	0.3829	0.3830	0.3834	0.3861	0.3979	0.3558	0.3260

Notes: The unit of observation is a crop-origin-destination triplet. All possible two-way fixed effects are included in all specifications. CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. The sample restriction, measurement change, or included control in each specification is noted by a check mark below the corresponding coefficient. The outcome is an indicator that equals one if any variety transfer has taken place. Standard errors are double-clustered by origin and destination.

Table A8: Agro-climatic Mismatch and Technology Transfer

	(1)	(2)	(3)	(4)
	Dependent Variable is Any Technology Transfer (0/1)			
CPP Mismatch (0-1)			-0.0306	-0.0314
			(0.0137)	(0.0139)
Agro-Climatic Mismatch		-0.0173		-0.0169
		(0.0045)		(0.0045)
Mismatch in:				
Soil pH	-0.0031		-0.0030	
	(0.0015)		(0.0015)	
Soil Silt Content	0.0016		0.0017	
	(0.0025)		(0.0025)	
Soil Clay Content	0.0003		0.0003	
	(0.0022)		(0.0022)	
Soil Coarse Fragment Content	0.0001		0.0001	
	(0.0015)		(0.0015)	
Available Water Capacity	-0.0022		-0.0022	
	(0.0021)		(0.0021)	
Elevation	-0.0027		-0.0027	
	(0.0014)		(0.0014)	
Ruggedness	-0.0007		-0.0006	
	(0.0011)		(0.0011)	
Growing Season Length	-0.0003		-0.0002	
	(0.0021)		(0.0021)	
Temperature	-0.0072		-0.0071	
	(0.0028)		(0.0028)	
Precipitation	-0.0089		-0.0089	
	(0.0035)		(0.0035)	
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	Yes
Country Pair Fixed Effects	Yes	Yes	Yes	Yes
Observations	153,878	153,890	153,026	153,038
R-squared	0.4066	0.4064	0.4069	0.4068

Notes: The unit of observation is a crop-origin-destination. Mismatch in agro-climatic features are estimated by first calcualting the value of each characteristic in the land area devoted to each crop in each country, as recorded by the EarthStat database, and then taking the normalized difference betweeen each pair of countries for each crop. Total agro-climatic mismatch is sum of the normalized components (those listed on the left). CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. The dependent variable is an indicator that equals one if any variety transfer has taken place. Standard errors are double-clustered by origin and destination.

Table A9: List of Crop-Specific Technology Leaders

Leader Name	Number of Crops
United States of America	30
France	28
The Netherlands	25
Japan	18
Russia	16
Spain	12
Germany	9
Australia	9
Brazil	8
Italy	8
Mexico	8
Czechia	6
United Kingdom	5
South Korea	4
Poland	3
Argentina	3
Turkey	3
Slovenia	2
Ecuador	2
Denmark	2
Colombia	2
New Zealand	1
Belarus	1
Hungary	1
Bulgaria	1
Morocco	1
South Africa	1
China	1
Kenya	1
Canada	1

Notes: The left column lists all the countries that are ever identified as a crop-specific leader country in our main analysis (i.e., as one of the top two variety developers for that crop). The right column notes the number of crops for which that country is idetified as one of the technology leaders.

Table A10: CPP Mismatch Reduces Area Harvested

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Area Harvested							
	CPP Mismatch with the Estimated Frontier				CPP Mismatch with the US			
CPP Mismatch (0-1)	-7.139	-7.020	-7.200	-5.837	-9.517	-12.080	-9.541	-7.855
	(0.941)	(0.725)	(0.437)	(0.496)	(1.212)	(2.892)	(0.595)	(0.635)
log(FAO-GAEZ-Predicted Output)		0.363				0.303		
		(0.0487)				(0.0768)		
Included in LASSO Pool:								
Top CPP Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Ecological Features x Crop Fixed Effects	-	-	No	Yes	-	-	No	Yes
Controls in LASSO Pool	-	-	335	3935	-	-	335	3935
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,469	2,268	6,474	5,748	6,675	2,268	6,683	5,908
R-squared	0.609	0.603			0.612	0.612		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP mismatch with the estimated set of technological leader countries and columns 5-8 use CPP mismatch with the US. Columns 1-2 and 5-6 report OLS estimates and columns 3-4 and 7-8 report post double LASSO estimates. Country and crop fixed effects are included in all specifications, and included in the amelioration set in the post-double LASSO specifications. The Top CPPs are defined as the top 200 CPPs defined by (i) the number of countries in which they are present and (ii) the number of host crops that they infect. Since the two sets overlap, the total number is 335. The set of ecological features includes: temperature, precipitation, elevation, ruggedness, growing season days, soil acidity, soil clay content, soil silt content, soil coarse fragment volume, and soil water capacity. Standard errors are double-clustered by crop and country.

Table A11: CPP Mismatch Reduces Agricultural Output: Crop $\times$ Continent Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Mismatch with the Estimated Frontier				CPP Mismatch with the US			
CPP Mismatch (0-1)	-8.780	-8.198	-6.999	-6.385	-8.809	-9.831	-8.780	-8.198
	(0.769)	(0.742)	(0.595)	(0.614)	(1.124)	(2.608)	(0.769)	(0.742)
log(FAO-GAEZ-Predicted Output)		0.273				0.239		
		(0.0770)				(0.0704)		
Included in LASSO Pool:								
Top CPP Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Ecological Features x Crop Fixed Effects	-	-	No	Yes	-	-	No	Yes
Crop x Continent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,631	2,334	6,696	5,903	6,844	2,334	6,920	6,069
R-squared	0.679	0.689			0.680	0.694		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP mismatch with the estimated set of technological leader countries and columns 5-8 use CPP mismatch with the US. Columns 1-2 and 5-6 report OLS estimates and columns 3-4 and 7-8 report post double LASSO estimates. Country and crop-by-continent fixed effects are included in all specifications, and included in the amelioration set in the post-double LASSO specifications. The Top CPPs are defined as the top 200 CPPs defined by (i) the number of countries in which they are present and (ii) the number of host crops that they infect. Since the two sets overlap, the total number is 335. The set of ecological features includes: temperature, precipitation, elevation, ruggedness, growing season days, soil acidity, soil clay content, soil silt content, soil coarse fragment volume, and soil water capacity. Standard errors are double-clustered by crop and country.

Table A12: CPP Mismatch and Agricultural Output: Country-Level Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	Panel B: CPP Mismatch with the Estimated Leader Set							
CPP Mismatch (0-1)	-6.963	-6.838	-7.351	-7.206	-6.895	-7.172	-7.337	-7.250
	(0.934)	(0.879)	(1.029)	(1.065)	(0.980)	(1.011)	(1.058)	(1.743)
Observations	6,693	6,458	6,227	4,765	6,499	5,838	3,631	2,864
R-squared	0.600	0.632	0.611	0.633	0.613	0.623	0.669	0.781
	Panel A: CPP Mismatch with the US							
CPP Mismatch (0-1)	-9.122	-8.849	-9.573	-9.323	-9.186	-9.661	-10.100	-10.830
	(1.152)	(1.105)	(1.217)	(1.345)	(1.221)	(1.316)	(1.295)	(2.115)
Observations	6,915	6,678	6,433	4,949	6,719	6,032	3,729	2,946
R-squared	0.600	0.632	0.612	0.634	0.614	0.626	0.671	0.786
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log Per Capita GDP x Crop FE	No	Yes	No	No	No	No	No	Yes
Trade Share (% GDP) x Crop FE	No	No	Yes	No	No	No	No	Yes
Gini Coefficient x Crop FE	No	No	No	Yes	No	No	No	Yes
Share Arable Land x Crop FE	No	No	No	No	Yes	No	No	Yes
log Agricultural Value Added x Crop FE	No	No	No	No	No	Yes	No	Yes
R&D Share (% GDP) x Crop FE	No	No	No	No	No	No	Yes	Yes

Notes: The unit of observation is a crop-country pair. Panel A uses CPP mismatch with the estimated set of technological leader countries and Panel B uses CPP mismatch with the US. Crop and country fixed effects are included in each specification. The additional controls included in each specification are noted at the bottom of the column and all take the form of a country-level characteristic interacted with a full set of crop fixed effects. Standard errors are double-clustered by crop and country.

Table A13: CPP Mismatch Reduces Output: Crop Heterogeneity

	(1)	(2)	(3)
Crop characteristic:	Staple Crop Indicator	GMO Indicator	High Innovation Indicator
CPP Mismatch (0-1) x Crop Characteristic	-4.8595	-3.3648	-2.2156
	(1.4716)	(0.9374)	(1.1095)
Country Fixed Effects	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes
Observations	6,704	6,704	6,704
R-squared	0.604	0.602	0.603

Notes: The unit of observation is a crop-country pair. Both country and crop fixed effects are included in all specifications and the outcome variable is log of crop-country output. CPP mismatch is constructed at the crop-country-pair level as one minus the number of common CPPs normalized by the square root of the product of the number of CPPs in the origin and destination. Each panel reports the coefficient on an interaction between CPP mismatch and the crop-level indicator listed at the top of the column. "High Innovation" means that the crop is in thee top 10% of total global variety releases. Standard errors are double-clustered by country and crop.

Table A14: Historical Green Revolution Breeding Sites

(1)	(2)
Green Revolution Breeding Sites	
Crop	Site Location
Wheat	Mexico (CIMMYT)
Maize	Mexico (CIMMYT)
Sorghum	India (ICRISAT)
Millet	India (ICRISAT)
Beans	Colombia (CIAT)
Potatoes	Peru (CIP)
Cassava	Colombia (CIAT)
Rice	Philippines (IRRI)

Notes: Column 1 reports the crops included in our analysis of the Green Revolution and column 2 reports the main breeding site during the Green Revolution for each crop, along with the corresponding IARC.

Table A15: Growth of US Biotechnology and Changes in Global Production

	(1)	(2)	(3)	(4)
	Δ log Output		Δ log Area Harvested	
	Panel A: Direct Effects			
CPP Mismatch with the US	-0.999	-0.974	-1.004	-1.044
	(0.520)	(0.572)	(0.502)	(0.533)
CPP Mismatch with the EU	0.644	0.251	0.352	0.222
	(0.512)	(0.531)	(0.529)	(0.534)
Crop Fixed Effects	Yes	-	Yes	-
Country Fixed Effects	Yes	Yes	Yes	Yes
Crop x Continent Fixed Effects	-	Yes	-	Yes
p-value, Dist US - Dist EU	0.097	0.249	0.172	0.216
Observations	6,414	6,338	6,183	6,107
R-squared	0.281	0.366	0.262	0.353
	Panel B: Crop Heterogeneity			
CPP Mismatch with the US	-0.634	-0.798	-0.819	-0.839
	(0.299)	(0.316)	(0.272)	(0.305)
CPP Mismatch with the US x Major US Field Crop	-1.161	-2.374	-2.208	-3.877
	(0.898)	(1.091)	(0.986)	(1.394)
Crop Fixed Effects	Yes	-	Yes	-
Country Fixed Effects x Major US Field Crop Indicator	Yes	Yes	Yes	Yes
Crop x Continent Fixed Effects	No	Yes	No	Yes
Observations	6,380	6,304	6,137	6,061
R-squared	0.312	0.393	0.292	0.379

Notes: The unit of observation is a country-crop pair. In columns 1-2, the dependent variable is the change in log output from the 1990s to 2010s and in columns 3-4 it is the change in log area harvested from the 1990s to 2010s. All columns include crop and country fixed effects, as well as the pre-period value of the dependent variable, and columns 2 and 4 also include crop by continent fixed effects. The major US field crops are corn, wheat, soybeans, and cotton. Standard errors are double-clustered by country and crop.

References

Batjes, N. H., Ribeiro, E., and Van Oostrum, A. (2020). Standardised soil profile data to support global mapping and modelling (WoSIS snapshot 2019). *Earth System Science Data*, 12(1):299–320.

Bazzi, S., Gaduh, A., Rothenberg, A. D., and Wong, M. (2016). Skill transferability, migration, and development: Evidence from population resettlement in Indonesia. *American Economic Review*, 106(9):2658–98.

Bustos, P., Caprettini, B., and Ponticelli, J. (2016). Agricultural productivity and structural transformation: Evidence from Brazil. *American Economic Review*, 106(6):1320–1365.

Duvick, D., Smith, J., Cooper, M., and Janick, J. (2004). Long-term selection in a commercial hybrid maize breeding program. *Plant Breeding Reviews*, 24:109–151.

Evenson, R. E. and Gollin, D., editors (2003). *Crop variety improvement and its effect on productivity*. CABI Publishing, Cambridge, MA, USA.

Kantor, S. and Whalley, A. (2019). Research proximity and productivity: long-term evidence from agriculture. *Journal of Political Economy*, 127(2):819–854.

Monfreda, C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22(1).

National Center for Atmospheric Research Staff (Eds) (2020). The Climate Data Guide: Global (land) precipitation and temperature: Willmott & Matsuura, University of Delaware. Accessed from: https://climatedataguide.ucar.edu/climate-data/global-land-precipitation-and-temperature-willmott-matsuura-university-delaware.

Nunn, N. and Puga, D. (2012). Ruggedness: The blessing of bad geography in Africa. *Review of Economics and Statistics*, 94(1):20–36.

Parente, S. L. and Prescott, E. C. (1994). Barriers to technology adoption and development. *Journal of Political Economy*, 102(2):298–321.

Reynolds, M. P. and Borlaug, N. (2006). Impacts of breeding on international collaborative wheat improvement. *The Journal of Agricultural Science*, 144(1):3–17.

Riley, S. J., DeGloria, S. D., and Elliot, R. (1999). Index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences*, 5(1-4):23–27.

Sotelo, S. (2020). Domestic trade frictions and agriculture. *Journal of Political Economy*, 128(7):2690–2738.