Inappropriate Technology: Evidence from Global Agriculture*

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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 inappropriate technology hypothesis in agriculture by using mismatch in the presence of crop pests and pathogens (CPPs) as a shifter of technology's inappropriateness and investigating its effect on technology diffusion and productivity. CPP mismatch reduces plant-variety transfer at the crop-by-country-pair level, particularly from innovation-intensive origins. CPP mismatch with these innovation-intensive countries reduces crop production. Our estimates, combined with a model, imply that inappropriateness reduces global productivity by 58% and increases cross-country disparities by 15%.

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Research and development (R&D), which drives technological progress, is concentrated in a small set of countries (Boroush, 2020). To what extent does this phenomenon underlie global productivity disparities? One school of thought starts from the premise that the most transformative technological knowledge is broadly applicable and easily transmittable. It concludes that technology diffusion from an innovation-intensive frontier can erode global disparities in the long run, and disparities in R&D are only a temporary obstacle to convergence.[1] In this framework, removing barriers to technology adoption is the key policy solution for low productivity. A second, contrasting school of thought emphasizes that new technologies are attached to specific conditions and characteristics of production (Griliches, 1957; Atkinson and Stiglitz, 1969). Variations of the *inappropriate technology hypothesis* state that frontier innovators' focus on developing technology that matches local conditions and characteristics severely inhibits that technology's diffusion to, and productivity benefit in, other contexts (Stewart, 1978; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001). Therefore, even with frictionless technology adoption, the direction of innovation in the frontier causes productivity to persistently differ across places and to cluster in those "similar" to R&D leaders. The quantitative relevance and global incidence of these predictions, however, remain mostly unknown.

One sector in which the premises of the inappropriate technology hypothesis seem to loom especially large is agriculture. This may be best illustrated via an example. The Corn Rootworm is nicknamed the "Billion-Dollar Bug" in the United States for its impact on corn production (Nordhaus, 2017). Developing technology that confers resistance against this evolving foe is the focus of a far-reaching innovation industry, an important achievement of which is the development of genetically modified varieties designed to be toxic specifically to Corn Rootworms without damaging other fauna (Bessin, 2019). But since these modern tools are necessarily not as effective against other pests, global producers facing different, untargeted pests may be left without comparably productive technology. For instance, genetically modified corn varieties are less effective at controlling the Maize Stalk Borer, a pest endemic to sub-Saharan Africa that is estimated to destroy 10% of Kenyan corn every year (Campagne et al., 2017; Ongamo et al., 2016). In this example, a difference in which pests are locally present, combined with the uneven focus of innovation across ecological threats, mediates how new technology affects global productivity.

Beyond such case-study evidence for a few crops and plant varieties, however, little is known about the effects of inappropriate technology in global agriculture. In particular, does the endogenous inappropriateness of technology systematically reduce the global diffusion of agricultural innovation, most of which originates in a handful of countries?[2] And does the same force explain a meaningful amount of the immense cross-country disparities in agricultural productivity, which are even larger than those in manufacturing (Caselli, 2005)?

This paper investigates each pillar of the inappropriate technology hypothesis in the context of global agriculture and plant biotechnology. Motivated by evidence in agricultural science that

[1] Eaton and Kortum (1996) and Barro and Sala-i Martin (1997) model how free diffusion of ideas can sustain international convergence in Neoclassical endogenous growth models.

[2] Over 50% of private R&D occurs in North America (Fuglie, 2016), and most countries in sub-Saharan Africa have no private sector investment (Access to Seeds Foundation, 2019). Public-sector and other non-profit research also concentrate in wealthy countries (see, e.g., Beintema et al., 2012; Vidal, 2014).

crop pests and pathogens (CPPs) are both pre-eminent threats to agricultural productivity and targets for biotechnological innovation, we compile systematic data on the global distribution and host-plant specificity of all known CPPs and develop a measure of crop-by-country-pair-level *CPP mismatch*. Using CPP-level distribution data, we verify that global R&D is heavily biased toward CPP threats present in high-income countries. We then present two main results documenting the consequences of inappropriate technology, using CPP mismatch as a predetermined shifter of technologies' potential inappropriateness across locations and crops. First, CPP mismatch reduces the cross-country diffusion of novel crop varieties, especially from more to less innovative countries. Second, CPP mismatch with those innovative countries reduces crop-specific production. We interpret these results via a model which endogenizes global agricultural productivity as the product of unevenly appropriate innovation. Combining our empirical estimates with the model, we quantify the aggregate productivity effect of the inappropriate-technology mechanism and study the effects of counterfactual changes to global research and ecology. Taken together, these results provide strong evidence for the inappropriate technology hypothesis—linking its premises to its predictions and productivity effects—and provide a framework to measure its incidence in a critical sector.

Model. We begin by developing a model of inappropriate technology in agriculture, to introduce the key economic mechanisms of the inappropriate technology hypothesis and generate estimable equations with model interpretations. Farmers around the world choose which crops to grow and what international technologies to use. Innovators in each country invest in improving their technology's adaptation to location- and crop-level environmental features. This process has local spillovers, which capture the fact that local knowledge and access to test fields or genetic material make it easier to develop technology adapted to the immediate environment. These spillovers guide innovators toward developing technology adapted to the local environment and hence endogenously "inappropriate" for dissimilar environments. As a result, global production is distorted toward crop-locations with environmental conditions resembling those in the most research-productive countries. We show how the strength of these effects hinges on the extent of knowledge spillovers and the relative importance of context-specific versus context-neutral components of technology. We then write the model's equilibrium conditions describing technology diffusion and production as regression equations, which we estimate in the empirical analysis.

Measurement. We next introduce our data on the global distribution and host-plant species of all known CPPs—including viruses, bacteria, parasitic plants, insects, and fungi—compiled from the Centre for Agriculture and Bioscience International's (CABI) Crop Protection Compendium (CPC). These data are based on expert review of published literature in plant pathology and agronomy (Pasiecznik et al., 2005), and they are used to comprehensively measure the global distribution of plant ecosystem threats in ecological sciences (e.g., Savary et al., 2019). As alluded to in our earlier example, CPPs are a dominant source of production losses, estimated to reduce annual global output by 50-80% (Oerke and Dehne, 2004), and CPP resistance has been a key focus of both traditional plant breeding (Collinge, 2016) and modern transgenic crop development (Dong and Ronald, 2019). Methodologically, our focus on CPPs, rather than other environmental conditions, has two key

benefits. First, CPPs can be directly linked to both specific locations and host plants, generating precise variation across both locations and crops. Second, references to unique CPPs in innovation data can be used to directly measure disparities in research across location-specific threats.[3]

Using these data, we construct our *CPP mismatch* measure of the potential inappropriateness of context-specific technology across locations and crops based on the differential prevalence of CPPs. CPP mismatch summarizes differences in CPP species composition at the level of crops and country pairs using techniques from population ecology (Jost et al., 2011). We use CPP mismatch as our main measure of "potential inappropriateness" of a crop-specific technology adapted to one CPP environment and applied in another. This measure incorporates variation across both country pairs, which have different local CPPs, and across crops, which are host plants to different CPPs.

As a prelude to our main analysis, we first use the CPP presence data to quantitatively validate that agricultural technology is adapted toward CPP presence and, globally, skewed toward rich-world CPP threats. We measure CPP-level innovation by the number of global agriculture patents, in biological and chemical classifications, that mention a specific CPP by name. One-third of all patents mention at least one CPP, consistent with their centrality for agricultural technology. Global patenting activity is highly skewed toward CPPs that are present in rich, research-intensive countries. We show that this finding is explained by the interaction of disproportionate focus on locally present threats with the uneven global distribution of patenting, consistent with our model.

Main Results. Having validated the premise that agricultural technology is adapted to local environmental conditions, as we measure them, we now turn to our first main question: how does inappropriateness shape global technology diffusion? To directly measure crop-specific technology transfer, we construct a unique data set on all international instances of intellectual property (IP) protection for agricultural biotechnology using proprietary data acquired from the International Union for the Protection of New Varieties of Plants (UPOV), the non-governmental body tasked with codifying and administering IP protection for plant varieties. We use the UPOV's unique variety identifiers to track individual seed varieties from their first introduction to all other countries where they were subsequently transferred. We estimate the effect of CPP mismatch on technology transfer at the crop-by-country-pair level, making it possible for fixed effects to fully absorb any forces varying 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., physical or cultural distance).

We find that CPP mismatch substantially lowers cross-border transfer of technology. In our most conservative specification, CPP dissimilarities reduce international technology transfer by 30% for the median crop and country-pair. This mechanism operates on both the intensive and extensive margin of variety transfer. We next study how these effects depend on the innovation intensity of the origin country—in particular, is mismatch with particularly active innovators what drives gaps in access to technology, consistent with the inappropriate technology narrative? We identify the

[3]Nevertheless, to account for the importance of other environmental differences, we also develop measures of non-CPP, agro-climatic environmental differences (e.g., in temperature and soil characteristics) and study their effects on both technology diffusion and production via the inappropriate technology mechanism in Appendix B.2.

most active variety producers for each crop in the UPOV data and show that the marginal effect of CPP mismatch on technology transfer is considerably higher when the origin country is one of these frontier innovators. For example, the effect of mismatch with the top three variety producing countries is more than 17 times our baseline effect, while the effect of mismatch with countries outside the top three is statistically indistinguishable from zero.[4]

Our second main question is how inappropriateness shapes global production. The model predicts that countries should specialize in crops for which ecological conditions most resemble those in frontier, innovating locations. We measure "CPP mismatch with the frontier" as the average crop-specific mismatch with the most technology-intensive countries, as identified in our earlier analysis of variety transfer. We then estimate the effect of CPP mismatch with the frontier at the crop-by-country level, net of fixed effects at the country and crop levels. The main potential threat to identification, which is articulated by the model, is the possibility that innate environmental suitability is correlated with CPP mismatch. We develop two strategies to directly address this issue: (i) controlling for geographically-determined potential yield derived from the FAO GAEZ agronomic model and (ii) controlling for a large set of ecological features, separately for each crop, and the direct effect of each CPP, disciplining this high-dimensional variable set with LASSO.

We find that CPP mismatch with the frontier substantially reduces crop-specific production. Our baseline estimate implies that a one-standard-deviation increase in CPP mismatch with the frontier reduces crop-specific production by 0.43 standard deviations. The effect size is similar after flexibly controlling for innate suitability, using the strategies described above. If we impose the United States as the frontier innovator for all crops instead of relying on the data for this step, we estimate a comparable effect of frontier mismatch on production. In a falsification exercise, we re-estimate the baseline regression replacing our main independent variable with CPP mismatch to each country in the world. The effect of CPP mismatch with *non-frontier* countries is centered around zero, and our estimates are in the far tail of the effect size distribution, indicating that our findings capture the causal effect of ecological mismatch with research-intensive countries. We also find quantitatively similar effects of CPP mismatch on production *within* countries, using state-level production and CPP distribution data from India and Brazil. In this specification, we also include crop-by-country fixed effects, making it possible to fully rule out the possibility that our estimates are driven by omitted characteristics that vary across country-crop pairs.

We next study a natural follow-up question to our main, static analysis: how do changes in technological leadership, and hence the map of "mismatch with the frontier," dynamically affect production? To investigate this question, we exploit two natural experiments in which the global distribution of research effort shifted and document how these shifts in research affected patterns of production. Our hypothesis is that global production should shift toward locations for which

[4]One shortcoming of our variety-transfer analysis is that many countries in Africa are not in the data, because intellectual property protection for plants does not exist. To supplement this, we conduct two additional analyses. In Appendix B.4, we show how mismatch with the frontier reduces variety introduction in sub-Saharan Africa, measured by the CGIAR's Diffusion and Impact of Improved Varieties in Africa (DIIVA) project. In Appendix B.5, we show how mismatch reduces farmers' adoption of "Improved Seed Varieties" in eight African countries, measured by the World Bank's Living Standards Measurement Study Integrated Survey of Agriculture (LSMS-ISA).

newly-developed technology is most appropriate. We first study the Green Revolution of the 1960s and 1970s, an effort to shift agricultural innovation toward certain tropical regions. We document that this change in the global focus of innovation led to an expansion of modern variety adoption and crop-specific production in places with lower CPP mismatch with centers of Green Revolution breeding. Second, we focus on the rise of US biotechnology in recent decades. We find that lower CPP mismatch with the US is associated with expansions of production since 1990. These findings, together, demonstrate that the impact of local ecology on productivity changes over time as the focus of innovation shifts.

Quantification. We finally interpret our findings via the model to quantify their aggregate productivity consequences, in a framework that accounts for relevant general-equilibrium forces while remaining as transparently tied to the regression estimates as possible. Concretely, we calibrate the model to match our estimates of the effect of CPP mismatch on production and external estimates of the supply and demand elasticities, which discipline reallocation and price responses. To benchmark the importance of the inappropriate technology mechanism for the observed productivity distribution, we calculate productivity in an (intentionally extreme) counterfactual scenario of "removing inappropriateness" by eliminating the knowledge gap between frontier and non-frontier CPP research. A possible story underlying this scenario is that a set of donors provide large enough research subsidies to redirect frontier research and overcome the knowledge gap about non-frontier CPP threats. We estimate that inappropriateness reduces average global agricultural productivity by 58% and explains 15% of the distribution's inter-quartile range, a measure of cross-country disparities. These findings, while suggestive, are driven by the fact that the countries most ecologically different from the frontier, especially in Africa and Asia, are also the least productive today.

We conclude by studying three counterfactual experiments that more directly speak to the potential impacts of contemporary trends in research and ecology. First, we use the model to identify the countries in which research investment could have the largest possible spillover effect on global productivity after taking into account the global network of environmental mismatch. Our results convey large gains from focusing a "Second Green Revolution" in India, China, and parts of sub-Saharan Africa. Second, we measure the aggregate and distributional effects of the growing shift in global R&D toward large emerging economies, in particular, Brazil, Russia, India, and China (BRIC). This analysis shows that the growth of BRIC R&D is on net favorable for the world's least productive countries and could serve as a partial substitute for purely local R&D in low-income countries or targeted investment by philanthropic or public sector organizations. Finally, we study the consequences of an anticipated poleward shift in the habitable range of CPPs due to climate change (Bebber et al., 2013). Our results suggest that climate change could coordinate international research on a more common set of threats, and therefore that the inappropriate technology mechanism might ameliorate some of the direct productivity losses from higher temperatures.

Related Literature. This paper builds on a historic body of work on how the "appropriateness" of technology shapes productivity differences and technology diffusion (Griliches, 1957; Atkinson and Stiglitz, 1969; Stewart, 1978). Some recent work in this area has modeled the productivity

consequences of high income countries' developing capital- or skill-complementing technology that is less appropriate in poor countries (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 study the innovation and technology diffusion components of the inappropriate technology hypothesis. Our analysis parallels work arguing that differences in human disease environments around the world shape the focus of medical technology development (e.g., Kremer and Glennerster, 2004; Hotez et al., 2007, on "neglected tropical diseases"). In this literature's language, we document the relevance of neglected ecological threats as an important determinant of global agricultural productivity.

At the center of our analysis are the determinants and impacts of technology diffusion (Keller, 2004; Comin and Mestieri, 2014). Related work includes macro-level studies of technology diffusion in prior centuries (Comin and Hobijn, 2004, 2010; Comin and Mestieri, 2018; Giorcelli, 2019) and micro-level studies of technology upgrading in modern times (Bandiera and Rasul, 2006; Conley and Udry, 2010; Atkin et al., 2017; Verhoogen, 2021, for a review). While most work in this area focuses on the characteristics of producers, we suggest that the focus of innovators shapes patterns of global technology use. Relatedly, 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.[5]

Finally, we extend a large literature on the relationship between environmental conditions and development (e.g., Montesquieu, 1748; Kamarck, 1976; Bloom and Sachs, 1998; Gallup et al., 1999). This study's 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. However, 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—as the direction of innovation changes, so does the economic impact of specific geographies.

This paper is organized as follows. Section 1 describes our model. Section 2 provides background information and describes our measurement strategy. Sections 3 and 4 report our main results on international technology transfer and production. Section 5 presents our quantification and counterfactual analysis and Section 6 concludes.

1. Model

This section develops a model of inappropriate technology in agriculture. We use the model to introduce the key economic mechanisms of the inappropriate technology hypothesis and generate estimable equations with model interpretations. We estimate these equations in our main empirical analysis of technology diffusion (Section 3) and production (Section 4). We use the model interpretation of our estimates in order to study counterfactual scenarios in Section 5.

[5]Relatedly, Marenya and Barrett (2009a,b) find that heterogeneous potential returns affect fertilizer demand in Kenya.

1.1 Set-up

Production. 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 $i \in [\ell - 1, \ell)$. Each farm can produce any of the K crops with one of L production technologies, indexed by the country of origin ℓ'. Given a production technology, the farm purchases $X_{k,\ell',i} \in \mathbb{R}_+$ of a technological input (e.g., seed varieties). The input has price $q_{k,\ell',\ell} \in \mathbb{R}_+$ and destination-specific quality $\theta_{k,\ell',\ell} \in \mathbb{R}_+$, both of which we will endogenize. The output of farm i producing crop k with $X_{k,\ell',i}$ units of country-ℓ' technology is

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

where $\gamma \in (0, 1)$ measures the return to fixed factors versus technology; $\omega_{k,\ell} \in \mathbb{R}_+$ is average natural suitability for crop k in country ℓ; and $\varepsilon_{k,\ell',i} \in \mathbb{R}_+$ is an idiosyncratic perturbation with a Fréchet distribution with mean one and shape parameter $\eta > 0$. The random component is specific to and independent across crops k and production technologies ℓ'. We abstract from other input choices (e.g., fertilizer, mechanical harvesters, labor) or non-natural sources of productivity (e.g., human capital) for simplicity. In Appendix A.5, we show how a production technology with these additional inputs can be mapped to Equation 1 after enveloping over the other choices.

Farmers choose what crop to grow, from what country to source technology, and how much of the input to buy, given crop prices p_k and input prices $q_{k,\ell',\ell}$. In Lemma 1, stated and proven in the Appendix, we solve for farmers' optimal input choice and show that farmers choose a crop and technology pair to maximize productivity via the following program:

$$\max_{k,\ell'} \left\{ p_k^{\frac{1}{\gamma}} q_{k,\ell',\ell}^{-\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i} \right\} \tag{2}$$

Environmentally-Adapted Technology. There is a set of environmental characteristics indexed by the natural numbers $\mathbb{N} = \{1, 2, 3, \ldots\}$. Each location-by-crop pair is associated with a set $\mathcal{T}_{k,\ell} \subset \mathbb{N}$ of local environmental characteristics, normalized to size $T > 0$. As a leading example, which we will henceforth focus on, $\mathcal{T}_{k,\ell}$ is the set of locally present crop pests and pathogens (CPPs). Note that any direct productivity effects of these characteristics can be modeled in average natural suitability $\omega_{k,\ell}$.

A given technology, identified by its quality $\theta_{k,\ell',\ell}$, is described by a context-neutral characteristic, $A_{k,\ell'} \in \mathbb{R}$, and a collection of CPP-specific characteristics, $(B_{t,k,\ell',\ell})_{t \in \mathcal{T}_{k,\ell}} \in \mathbb{R}^T$. These characteristics combine to determine the overall productivity of the technology in the following way:

$$\theta_{k,\ell',\ell} = \exp\left(\alpha \log A_{k,\ell'} + \frac{1-\alpha}{T} \sum_{t \in \mathcal{T}_{k,\ell}} \log B_{t,k,\ell',\ell} \right) \tag{3}$$

where $\alpha \in (0, 1)$ parameterizes the relative importance of the context-neutral characteristic. High $A_{k,\ell'}$, by definition, boosts the productivity of technology in all locations ℓ. Each characteristic $B_{t,k,\ell',l}$, by contrast, affects productivity only if the CPP t is present. Finally, the two components are complementary to one another: high general productivity increases the marginal value of resistance

to CPP damage, and vice-versa.[6] To intensify the focus on incentives for technology's "appropriateness," we assume that the technology's context-neutral characteristic $A_{k,\ell'}$ is inelastically fixed while the context-specific characteristics $B_{t,k,\ell',\ell}$ are endogenously determined by innovators.

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

$$C_{k,\ell',t}(B) = e^{-\tau(B_{t,k,\ell',\ell'})} \frac{(B_{0,\ell'}B)^{1+\phi}}{T(1+\phi)} \tag{4}$$

where $\phi > 0$ is an 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.[7] The spillover may capture both knowledge about local conditions and physical inputs with a public-good property like local test fields and genetic material. This aspect of agricultural technology development is well-documented in the context of private-sector, public-sector, and philanthropically supported research.[8] We will discuss more examples in Section 2.1.

We assume that the innovator prices the technological good at markup $\mu_{\ell'}$ over its marginal cost, which is normalized to one. In Appendix A.4, we show how this nests the conventional assumption of monopoly pricing while also allowing us to model less profit-motivated innovators, like public sector research groups or non-governmental organizations. The monopoly pricing case may be appropriate to model large biotechnology firms in the United States, while the less profit-motivated case may be appropriate for modeling, for example, countries in Africa which have essentially no private-sector breeders (Access to Seeds Foundation, 2019) but do have government-sponsored research programs.[9] Finally, we assume that ℓ'-innovators receive fraction $\exp(-\rho_{\ell,\ell'}) \leq 1$ of potential country-ℓ net revenue due to trade, licensing, and IP costs.

Innovators in each country ℓ' choose, for each (k, ℓ) destination market, the vector of CPP-specific research effort, $\vec{B}_{k,\ell',\ell} = (B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}$, to maximize revenues net of costs, given the pricing policy described above and conjectures for crop prices, the destination's productivity, and local research

[6] One illustration of this "two-component" structure comes from Reynolds and Borlaug (2006)'s account of wheat development at the CIMMYT. The authors write that a key challenge was to both improve yields by incorporating a specific semi-dwarfism trait ("A"), valuable in any environment, and to increase resilience to damaging fungal wheat rusts ("B"), specific to certain environments. Moreover, the value of better resisting wheat rust increased when the plant had higher overall yield (complementarity).

[7] We assume that $\phi > (1-\alpha)\eta - 1$, which is sufficient for the innovator's problem to be concave.

[8] 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. Duvick et al. (2004) highlights the importance of similar inputs for maize breeding at the private breeder Pioneer Hi-Bred.

[9] Specifically, in that appendix, we micro-found $\mu_\ell \in (1, (1-\gamma)^{-1}]$ by assuming the innovator behaves with *conduct parameter* $\sigma_{\ell'} \in [1, \infty)$ (Bresnahan, 1989).

on each CPP. In Lemma 3 in the Appendix, we re-write the innovator's problem as

$$\max_{\vec{B}_{k,\ell,\ell'}} \left\{ e^{-\rho_{\ell',\ell}} R(\vec{B}_{k,\ell',\ell}; \hat{p}_k, \hat{\Xi}_\ell, \mu_{\ell'}) - \sum_{t \in \mathcal{T}_{k,\ell}} e^{-\tau(\hat{B}_{t,k,\ell',\ell'})} \frac{(B_{0,\ell'} B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)} \right\} \tag{5}$$

where $R(\cdot)$ gives the 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.

An important object, due to its centrality to the knowledge spillover, is local research in CPP-specific technology. Intuitively, this can be especially high in certain countries ℓ' for three reasons embedded in the set-up. First, these countries may have low iceberg costs $\rho_{\ell',\ell'}$—for instance, due to effective IP protection (see, e.g., Diwan and Rodrik, 1991; Acemoglu and Zilibotti, 2001). Second, innovators in these locations may have systematically lower costs of research, or lower $B_{0,\ell'}$—for instance, due to easily accessible physical and human capital or high-quality government institutions.[10] Third, these countries may have a large endowment of productive land, or high $\omega_{k,\ell'}$.[11] Our main analysis will be largely agnostic about the sources of R&D inequalities and focus instead on their implications for technology diffusion and global productivity.

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 $(X_{k,\ell',\ell})$, prices (p_k), and CPP technology development $(B_{t,k,\ell',\ell})$ 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.

1.2 Main Predictions

We now describe the model's predictions for technology diffusion and global production. All proofs are given in Appendix A.

Technology Diffusion. Let $\delta_{k,\ell',\ell}$ be the fraction of k-CPPs that are not shared between locations ℓ and ℓ', or $\delta_{k,\ell',\ell} = 1 - \frac{1}{T}|\mathcal{T}_{k,\ell} \cap \mathcal{T}_{k,\ell'}|$. Our first result describes how the total quantity of technology transferred for crop k from location ℓ' to location ℓ, or $X_{k,\ell',\ell} = \int_{\ell-1}^{\ell} X_{k,\ell',i}\, \mathrm{d}i$, depends negatively on CPP mismatch $\delta_{k,\ell',\ell}$:

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

$$\log X_{k,\ell',\ell} = \beta_{k,\ell'} \cdot \delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell,\ell'} \tag{6}$$

where the χ are additive effects varying at the indicated level and

$$\beta_{k,\ell'} = -\frac{\eta(1-\alpha)\tau(B_{k,\ell'})}{1+\phi-(1-\alpha)\eta} \leq 0 \tag{7}$$

[10] Cirera and Maloney (2017) survey how a lack of these factors can impede R&D in low-income countries. Gorodnichenko and Schnitzer (2013) study the role of financial frictions for the same.

[11] We document this "market size effect" for seed variety development in Appendix B.3.

where $B_{k,\ell'}$ is the extent of (k, ℓ') CPP research on CPPs present in ℓ'.

Mismatch depresses technology transfer, or $\beta_{k,\ell'} < 0$, if both of the following two conditions hold: there is some context-specificity of technology ($\alpha < 1$) and some knowledge spillover ($\tau > 0$). Absent context-specific technology, innovation is biased toward the crops over-represented in large markets, but not the large-market ecological conditions for growing those crops. Absent the knowledge spillover, innovation would concentrate on large-market ecological conditions, but this would have no external effects on the rest of the world. With both ingredients ($\alpha < 1$ and $\tau > 0$), innovators in country ℓ' have a "knowledge gap" about local ecological characteristics relative to others and therefore produce more technology for ecologically similar destinations.

The magnitude of the effect of mismatch on technology diffusion, or $|\beta_{k,\ell'}|$, increases in the sending country's CPP research intensity $B_{k,\ell'}$ if and only if τ is increasing. In this case, consistent with the inappropriate-technology narrative, environmental mismatch with the most active innovating countries is the most costly for technology diffusion.[12] The model links this narrative to the idea that the most "developed" technology, with high B, also has the highest potential knowledge spillover.

In our empirical analysis, we will estimate Equation 6 treating counts of uniquely identified seed varieties transferred across borders as a proxy for $X_{k,\ell',\ell}$ and using our measurement of CPP mismatch as a proxy for $\delta_{k,\ell',\ell}$. We will also directly investigate whether the effect of environmental differences on technology transfer is exaggerated when the origin country is on the "research frontier," measured via various empirical proxies.

Specialization and Productivity. We next study the impact of inappropriate technology on production. We first define the *crop technology index* $\Theta_{k,\ell} = (\sum_{\ell'=1}^{L} \theta_{k,\ell',\ell}^{\eta})^{1/\eta}$. The following result summarizes the model predictions:

Proposition 2. *Production of crop k in country ℓ, $Y_{k,\ell} > 0$, is given by*

$$\log Y_{k,\ell} = \eta \log \Theta_{k,\ell} + \tilde{\chi}_k + \tilde{\chi}_\ell + \eta \log \omega_{k,\ell} \tag{8}$$

Production increases in the index of technology, and hence in the quality of each sending country's technology in the local environment. The elasticity η with respect to physical productivity relates to the extent of plot-level heterogeneity: when η is higher, and this heterogeneity is lower, then production more sharply re-allocates in response to small productivity changes (as in Eaton and Kortum, 2002; Costinot et al., 2016). In Equation 8, crop and country fixed effects respectively absorb prices and average local revenue productivity. The "residual," net of technology and these fixed effects, is a re-scaling of local innate productivity $\omega_{k,\ell}$.

In the proof of this result in Appendix A.3, we derive also the model's predictions for physical yield and planted area. A key issue that our model handles precisely is selection along unobserved dimensions of land quality. While secularly boosting the productivity of a given crop (e.g., by improving available foreign technology) expands production possibilities, it does not necessarily increase average productivity due to the expansion of land onto increasingly less suitable land.

[12] A lower elasticity of supply (ϕ) and higher elasticity of demand (η) also amplify this effect for intuitive reasons.

When these selection effects are disciplined by the Fréchet model, both production and area have the same elasticity η with respect to the productivity index $\Theta_{k,\ell}$.

In Section 4, we will estimate Equation 8 using CPP mismatch with an empirically identified technological frontier to span $\log \Theta_{k,\ell}$ and a variety of empirical strategies to span innate productivity $\omega_{k,\ell}$. This will allow us to directly measure the effect of inappropriateness on production choice and specialization. We will also directly test the model's predictions for area and yields to assess the validity of the specific Fréchet model for unobserved heterogeneity. In Section 5, we will use the estimates from this analysis plus the model structure to estimate effects on productivity.

1.3 Additional Results and Extensions

Before proceeding to the empirical analysis, we summarize two extensions in the Appendix.

Social vs. Private Incentives. Our main results were stated and proved as conditions for competitive equilibrium. In Appendix A.6 we present and discuss the social planner's equivalent first-order conditions for research. A key difference is that the planner internalizes the knowledge spillover. This creates incentives for researchers in all countries to research all pest and pathogen threats, including those most neglected in equilibrium.

An Alternative Source of Inappropriateness. Our baseline model allows innovators to develop technologies targeted at different parts of the world and generates local specificity via knowledge spillovers. In Appendix A.7, we derive analogs to the model's main predictions in an alternative model in which, following Acemoglu and Zilibotti (2001), innovation is possible only in one "frontier" country, and "copycat" innovators create equivalent, lower-cost technologies in all other countries. In practice, governments, universities, or local firms may fulfill this copycat role. The analog to Proposition 1 shows that copycat technologies, which copy the $B_{t,k}$ of the frontier's technologies, are more locally productive when local conditions match the frontier's. Overall, we view the two modeling approaches as broadly complementary for understanding productivity differences, but argue that our baseline approach is more useful for studying technology diffusion.

2. Background and Measurement: Agricultural Pests and Pathogens

In this section, we provide background information about pest targeting in biotechnology and provide a detailed description of our main data source. We then document CPP-level disparities in international research and introduce our measure of inappropriateness based on the dissimilarity of CPP environments across crops and locations.

2.1 Pathogen Threats and Plant Breeding

Crop pests and pathogens (CPPs), which include 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), which represents "possibly the greatest threat to productivity" across all environments (Reynolds and Borlaug, 2006, p. 3). As

one example, the Western Corn Rootworm alone caused $1 billion in annual losses in the US and substantially more around the world 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 most fundamental technique for breeding favorable plant traits, including CPP resistance, is mass selection: saving the seeds of the "best" plants from a given crop cycle, re-planting them the next year, and repeating the process (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. This context-specificity of traditional breeding can severely inhibit the diffusion of agricultural technology (Moseman, 1970). Historically, adapting mass-selected crop lines to new contexts has required substantial lineage-specific investment, like "shuttle breeding" alternative generations in different locations (see, e.g., Reynolds and Borlaug, 2006, pp. 8-9).

More recently, genetic modification (GM) has been added to the crop development toolkit. The vast majority of modern GM technology has directly related to 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 process of natural selection in the field and consequent obstacles to breeding for non-local environments. But, in practice, GM technology has been used almost exclusively for solving the pathogen threats facing high-income countries (Herrera-Estrella and Alvarez-Morales, 2001).

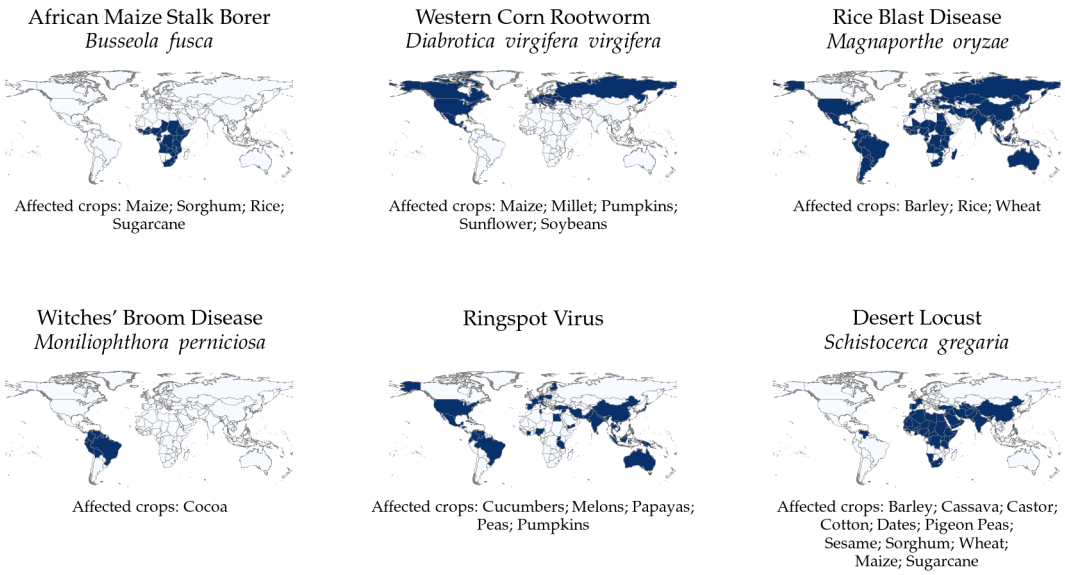
An illustrative case study of how modern plant varieties are "locally" targeted comes from Bt varieties, a large and celebrated class of genetically modified plants. Bt varieties are engineered to express crystalline proteins, cry-toxins, that are naturally produced by *Bacillus thuringiensis* bacteria ("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 Western Europe. In other parts of the world, however, frontier Bt maize is neither commonly used nor effective. For example, in South Africa there is widespread resistance to Bt maize and production damage caused by the African Maize Stalk Borer, which does not exist in the US but is widespread in sub-Saharan Africa (Campagne et al., 2017). Disparities in the appropriateness of GM technologies therefore emerge as a result of a focus on "rich-world pests."

We provide more examples and an extended discussion of the relationship between the global distribution of CPP threats and plant breeding in Appendix C.

2.2 Plant Pest and Pathogen Data: The Crop Protection Compendium

While the aforementioned examples highlight specific and extreme instances of pest-specificity, it is unclear whether they are representative of general biases in agricultural technology. Our analysis, unlike existing field tests of specific varieties, has the advantage of being able to estimate the average

Figure 1: Data on Example CPPs



Notes: Shading indicates country-level CPP presence according to the CABI Crop Pest Compendium (CPC).

effect of CPP mismatch across all crops and countries and connect it with an economic model to determine its aggregate consequences.

Our key source of information on the global distribution of crop pests and pathogens is the Centre for Agriculture and Bioscience International's (CABI) Crop Protection Compendium (CPC). This database is the "world's most comprehensive site for information on crop pests," and provides detailed information on the geographic distribution and host species set for essentially all relevant plant pests and pathogens. Construction of the database began in the 1990s as a collaboration between CABI, the UN Food and Agriculture Organization, and the Technical Centre for Agricultural and Rural Cooperation. The goal of the project is to develop comprehensive, global coverage of crop diseases in order to better manage food production. The CPC was compiled through extensive searches of existing crop 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).[13] In total, we compile information on 4,951 plant pests and pathogens, including viruses, bacteria, insects, fungi, and weeds.

For each species, the CABI-CPC provides two key pieces of information. First, it reports the CPP's global geographic distribution. Figure 1 displays the distribution map for six pests, including the Maize Stalk Borer and Western Corn Rootworm, which were referenced in previous examples. For most countries, CABI reports whether the pest is present or not present in the country as a whole. For a handful of large countries—including Brazil and India, which we return to later—CABI reports

[13]The CABI-CPC is commonly used for CPP measurement in population ecology and crop science (e.g., Bebber et al., 2013, 2014; Savary et al., 2019).

state-level data on the presence of each CPP.

Second, CABI 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 consumes maize, millet, pumpkins, sunflower, and soybeans, but not sorghum or sugarcane (Figure 1, top panel). Our data contain information on 132 host species that are major crops, cross-referenced against the crops used in our subsequent analyses of biotechnology intellectual property and production.

2.3 Measuring Inappropriateness: CPP Mismatch

Using the CABI CPC data, we develop our main measure of inappropriateness: *CPP mismatch*. In the model, the scalar summary of ecological difference was the measure of non-common CPP threats, $\delta_{k,\ell,\ell'}$. In the data, 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:

$$\text{CPP Mismatch}_{k,\ell,\ell'} = 1 - \frac{\text{Number of Common CPPs}_{k,\ell,\ell'}}{\left(\text{Number of CPPs}_{k,\ell} \times \text{Number of CPPs}_{k,\ell'}\right)^{1/2}} \tag{9}$$

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. In the language of ecology, as discussed in a review chapter on biological similarity by Jost et al. (2011), our CPP mismatch formulation in (9) is one of several standard divergence (one-minus-similarity) measures that satisfy basic properties of *density invariance*, *replication invariance*, and *monotonicity*. This means that the divergence or similarity measures provide consistent results regardless of the total number of species or population of any individual species in ℓ or ℓ'.[14]

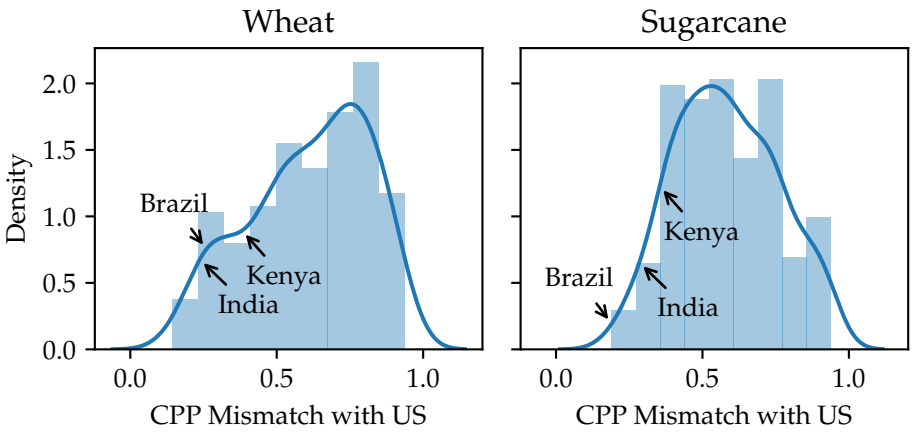
CPP mismatch varies at both the country-pair level, fixing crops, and the crop level, fixing country pairs. The *country-level variation* is illustrated Figure 1: different countries are endowed with different CPPs. The *crop-level variation* is due to the fact that each CPP only affects a particular set of crops. 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. To illustrate this variation, Figure 2 shows the histogram of all countries' CPP mismatch with the US for wheat and sugarcane and identifies the observations for Brazil, India, and Kenya. For wheat, Brazil is slightly more mismatched with the US than India, and Kenya is slightly more mismatched than Brazil. For sugarcane, however, India is substantially more mismatched than Brazil, and Kenya is substantially more mismatched than India. These two sources of variation allow us to fully absorb any differences across countries or

[14] We will also, as a robustness check, supplement our main measure with the simplest and oldest measure of divergence due to Jaccard (1900) which counts the fraction of non-shared species:

$$\text{CPP Mismatch}^{J}_{k,\ell,\ell'} = 1 - \frac{\text{Number of Common CPPs}_{k,\ell,\ell'}}{\text{Number of Unique CPPs}_{k,\ell\cup\ell'}} \tag{10}$$

This metric has the same range (0 to 1) and interpretation of extreme values as our baseline, but different properties for intermediate levels of similarity. Both this measure and our baseline correspond exactly to $\delta_{k,\ell,\ell'}$ in the model, in which the total measure of CPP threats is normalized to one in each country.

Figure 2: Example of CPP Mismatch Variation



Notes: Histogram (solid bars) and kernel density estimates (lines) for CPP Mismatch$_{\ell,\ell',k}$, where ℓ is the United States and k is the crop indicated in each graph. Values for India, Brazil, and Kenya are labeled.

crops in our analysis.

A natural question is what forces drive the international distribution of each CPP. The determinants of the cross-sectional distribution of each CPP are not well understood by ecologists, and 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, location fixed effects will make it possible to absorb any crop-invariant effects of the local environment. 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 B.2 for a discussion). Importantly also, Bebber et al. (2014) document that CPP distributions measured from the CABI CPC appear unrelated to patterns of trade, travel, or tourism, suggesting that human activity plays a limited role in shaping the cross-sectional distribution of CPPs on average.

Nevertheless, we use two additional strategies to fully purge our measure of inappropriateness of any potential consequences of human activity, and reproduce all estimates using these alternative measurement techniques. We describe these strategies here and reference them again when we discuss the robustness of our main results.

Directly Removing Eradications and Invasive Species. While our baseline measure of CPP mismatch is designed to capture the CPP differences around the world today, we use additional data from CABI to study the role of eradications and species invasions, and ultimately 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. In each part of our analysis, we reproduce our results using a broader definition of CPP mismatch that includes eradicated CPPs,

and the results are similar.[15] Second, to investigate the potential role of invasive species, which could be an important mechanism but also potentially endogenous to human behavior, we use the CABI Invasive Species Compendium (ISC) to identify all invasive and high-invasive-potential CPPs and drop them from the measurement of CPP mismatch (see Appendix Section B.1).

Agro-Climatic Mismatch. We also investigate the importance of non-CPP differences in geography, including temperature, precipitation, and soil characteristics, as alternative and predetermined shifters of appropriateness. Appendix Section B.2 discusses our measurement of crop-by-country-pair *agro-climatic mismatch*, and reports our main empirical results using agro-climatic mismatch as an additional determinant of inappropriateness. We find that agro-climatic mismatch inhibits technology transfer and reduces production, similar to our main results based on CPP mismatch reported in Sections 3 and 4. Replicating our main findings using the mismatch of fixed geographic characteristics builds confidence that our main results are not driven by idiosyncracies of CPPs or their measurement. We moreover find the effects of agro-climatic mismatch are largely independent from the effects of CPP mismatch for both outcomes. Agro-climatic mismatch, as we measure it, has a quantitatively smaller effect on technology transfer and production than CPP mismatch.

2.4 Validation: Disparities in Global Innovation Related to CPPs

Earlier in this section, we provided qualitative evidence that biological innovation is adapted to CPP environments and that global science and technology focuses predominately on rich-world CPPs. Using the CABI CPC data, we can validate these premises systematically. We identify all global biological or chemical agricultural patents in the *PatSnap* database by searching for the scientific name of each CPP in all patent titles, abstracts, and descriptions.[16] We also identify the country of origin of each patent using *PatSnap*'s determination of the inventor's location. We document three facts about patenting at the country-by-CPP level, all consistent with the premise of the inappropriate technology hypothesis.

First, a large share of global innovation is focused on CPPs; 33% of all global biological and chemical agricultural patents mention at least one CPP in our sample.

Second, innovators focus substantially more on locally present CPPs. This pattern is apparent in the raw patent data: on average, over 17 times more patented technologies are developed for locally present CPPs compared to CPPs that are not present in the country of interest (panel (a) of Figure 3). We investigate this pattern more precisely by estimating the following regression:

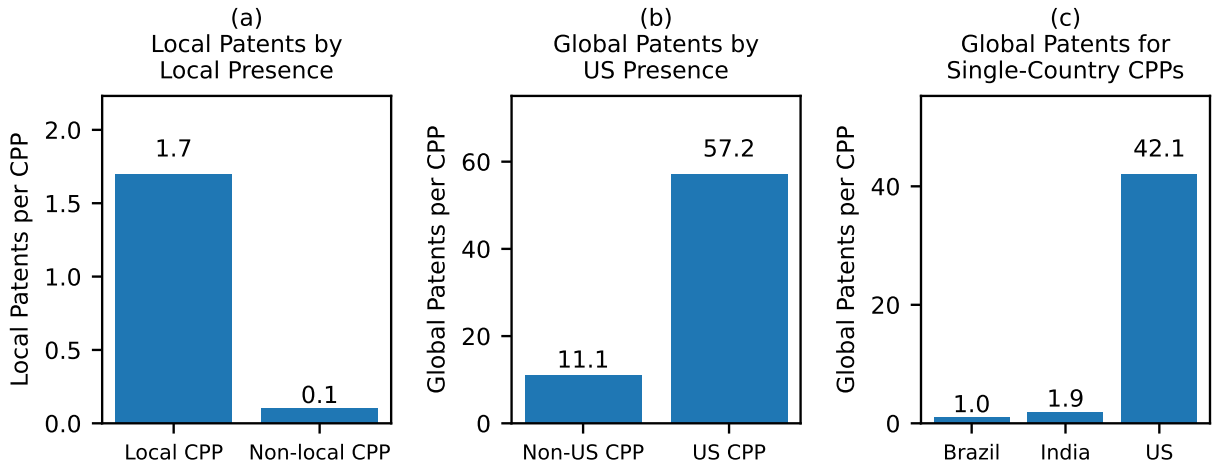
$$y_{\ell,t} = \xi \cdot \text{Local CPP}_{\ell,t} + \chi_\ell + \chi_t + \varepsilon_{\ell,t} \tag{11}$$

where the unit of observation is a CPP-year and $\text{Local CPP}_{\ell,t}$ is an indicator that equals one if CPP t is present in country ℓ. $y_{\ell,t}$ is the number of patented technologies developed in country ℓ related to CPP threat t, transformed by the inverse hyperbolic sine, and χ_ℓ and χ_t absorb country and CPP

[15] Such "eradication events" are rare. The number of CPP-country-crop triads increases by under 3% when using the "broad" CPP presence classification.

[16] We define biological/chemical agricultural patents as those in Cooperative Patent Classes A01H or A01N.

Figure 3: Global Patenting on CPPs



Notes: Graph (a) reports the average number of patented technologies developed in countries ℓ related to CPP threats t if the CPP is present (not present). Graph (b) reports the average number of patented technologies developed about CPPs that are not present in the US and CPPs that are present in the US. Graph (c) reports the number of patented technologies developed about CPPs that are present only in (i.e., endemic to) the countries specified on the x-axis.

fixed effects. ξ captures the extent to which innovation is disproportionately targeted toward local CPP threats. Table A2 reports our estimates. We estimate that $\xi > 0$ in Equation 11, and it remains large and significant focusing on either the intensive or extensive margin separately (columns 2-3).

Third, in the aggregate, substantially more technology is developed to combat CPPs that exist in high-income countries like the US. Panel (b) of Figure 3 demonstrates that CPPs present in the US are mentioned by over five times as many patents as those not present in the US. Table A3 reports estimates from an augmented version of (11) in which Local $\text{CPP}_{\ell,t}$ is interacted either with an indicator that equals one if ℓ is the US (columns 1-3) or (log of) per-capita GDP of ℓ (columns 4-6). The impact of a locally present CPP on innovation is substantially larger in high-income countries, consistent with greater overall R&D intensity. Finally, panel (c) of Figure 3 shows one particularly striking cut of the data: the number of patents about CPPs that are present *only* in the US dwarfs the number of patents for CPPs that are present only in Brazil or India, two large but less research intensive agricultural economies.

This analysis, taken together, documents that a large share of global agricultural innovation is focused on CPPs and that much of this research is highly localized. The result is a far greater focus on CPP threats present in high-income, research-intensive countries. These findings are consistent with the set-up of our model of endogenous technology development focused on local conditions.

3. Results: Inappropriateness and Technology Diffusion

In this section, we investigate the relationship between inappropriateness, measured using CPP mismatch, and technology diffusion, measured with a new database of the invention and inter-

national transfer of plant varieties. We find that CPP mismatch substantially lowers cross-border technology transfer, and that this effect is strongly driven by transfer from innovation-intensive origin countries. We corroborate these findings in additional analyses of variety introduction and adoption in Africa.

3.1 Data: The UPOV Plant Variety Database

We measure the development and international transfer of biotechnology using a novel dataset of all global instances of intellectual property protection for crop varieties. We obtained these data from The International Union for the Protection of New Varieties of Plants (UPOV), the inter-governmental organization tasked with designing, promoting, and administering systems of intellectual property protection for plant varieties around the world.[17] The data provide comprehensive coverage of all plant variety certificates, an internationally standardized form of intellectual property, across the member countries identified in the map in Figure A1.[18]

To be recognized by UPOV, a variety must be new, distinct, uniform (identical across plants within a generation), and stable (identical across generations). Since this set of variety characteristics is relatively straightforward to document, barriers to obtaining protection—in terms of both legal fees and the burden of documenting the inventive step—are limited. This helps ensure that the UPOV database captures a large share of varieties in circulation.[19] Finally, a breeder must protect a variety separately in each country where they want legal enforcement, meaning that 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.[20] That is, wherever in the world a denomination code is observed in the database, it corresponds to a single, unique plant variety. This allows us to track the diffusion of individual varieties across countries. The certificate data, when cross-linked to a list of crops and screened for duplicate entries, consists of 458,034 total variety registrations, spanning 62 countries, 109 crops, and 236,529 unique denominations.

Figure 4 displays a snapshot of the raw UPOV data. These five rows are from the section of the database on cotton varieties registered between 1999 and 2003. This example consists of three unique denominations (Sicot 41, Sicot 53, and Sicot 71) registered across three countries (Australia, Argentina, and Brazil). Sicot 53 cotton was first registered in Australia in 1999 and later in Brazil in 2003. Sicot 41 cotton was also introduced in Australia in 1999 and transferred to Argentina in 2001.

[17] Our project required a formal application process and approval from the UPOV Council.

[18] This set includes most of North and South America, Europe, West Africa, and East Asia. Notably missing are several large agricultural producers in South Asia, North Africa, and sub-Saharan Africa. We return to this topic in Section 3.4.

[19] This helps ameliorate concerns associated with measuring technology using patent data, which is often skewed toward large, private sector firms due to the high financial barriers to obtaining protection.

[20] This stipulation is described in the most recent revision of the UPOV Convention (Union for the Protection of New Varieties of Plants, 1991), and reaffirmed in the 2015 "explanatory notes" (Union for the Protection of New Varieties of Plants, 2015).

Figure 4: Example Rows from UPOV Data Set

UPOV Code	Country	Denomination	Botanical Name	Common Name	App. Date
GOSSY_HIR	AU	Sicot 53	Gossypium hirsutum	Cotton	14-Sep-99
GOSSY_HIR	AU	Sicot 41	Gossypium hirsutum	Cotton	14-Sep-99
GOSSY_HIR	AR	Sicot 41	Gossypium hirsutum L.	Algodonero	13-Aug-01
GOSSY_HIR	AU	Sicot 71	Gossypium hirsutum	Cotton	07-Aug-02
GOSSY_HIR	BR	Sicot 53	Gossypium hirsutum L.	Algodao	11-Nov-03

Finally, Sicot 71 cotton was introduced in Australia in 2002, but was never introduced in any other country.

More generally, for every unique denomination in the data, we identify a country of first appearance and define the country of first appearance as the origin country since this is likely to be the market for which the variety was first developed.[21] 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'. This is our primary measure of technology diffusion between country pairs at the crop level. For our main analysis, we focus on a static cross-section and sum over all final registrations after 2000. From our example above, Sicot 53 would count among the transferred cotton technologies from Australia to Brazil and Sicot 41 would count among the transferred cotton technologies from Australia to Argentina.

Appendix B.3 presents a more detailed analysis of the global direction of innovation in the UPOV variety database, mirroring our analysis of CPP-level patents in Section 2.4. Echoing the previous discussion about the concentration of innovation in richer countries, 67% of all recorded varieties are first reported in the United States, Canada, or a European Union member state.

3.2 Results: Inappropriateness Reduces Technology Diffusion

In this section, we investigate how inappropriateness affects technology transfer in our full sample of crops and country pairs. Our main estimating equation is the empirical analog of Equation 6 in Proposition 1:

$$y_{k,\ell',\ell} = \beta \cdot \text{CPP Mismatch}_{k,\ell',\ell} + \chi_{\ell,\ell'} + \chi_{k,\ell} + \chi_{k,\ell'} + \varepsilon_{k,\ell,\ell'} \tag{12}$$

where k indexes crops, ℓ indexes technology-receiving countries, and ℓ' indexes technology-sending countries. $y_{k,\ell',\ell}$ is a monotone transformation of the number of unique varieties of crop k developed in ℓ' and transferred to ℓ between 2000-2018. Since there are zeroes in the varieties data, we report the effect separately for the intensive margin with log biotechnology transfers, the extensive margin with an indicator for any transfer, and the inverse hyperbolic sine (asinh) transformation which blends the two margins. Our baseline specification includes all possible two-way fixed effects: origin-by-destination fixed effects, crop-by-origin fixed effects, and crop-by-destination fixed

[21] This avoids potential issues associated with using the country of the innovating firm or 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. Our strategy would correctly identify the intended beneficiary of this technology as Brazil, rather than the US.

Table 1: CPP Mismatch Inhibits International Technology Transfer

Dependent Variable:	(1) Biotech Transfer (asinh)	(2) Any Biotech Transfer (0/1)	(3) log Biotech Transfer
CPP Mismatch (0-1)	-0.0624**	-0.0275**	-1.202***
	(0.0235)	(0.0106)	(0.386)
Crop-by-Origin Fixed Effects	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes
Origin-by-Destination Fixed Effects	Yes	Yes	Yes
Observations	204,287	204,287	5,791
R-squared	0.439	0.383	0.797

Notes: The unit of observation is a crop-origin-destination. All possible two-way fixed effects are included in all specifications. The dependent variable is listed at the top of each column. Standard errors are double-clustered by origin and destination and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

effects.[22] Standard errors are double-clustered by origin and destination.

The coefficient of interest is β and the main hypothesis is that $\beta < 0$, or that the local focus and context specificity of innovation depresses technology diffusion. We may find no effect, however, if the context-specific component of technological progress or local research spillovers are relatively small, or if technology diffusion is sufficiently inelastic with respect to incentives. Due to the included fixed effects, any confounding force that could bias our estimate of β would have to vary across crops and within country-pairs. For example, any differences in market size, income, or other input use at the origin or destination, and any variation in distance or connectedness across country pairs, are fully absorbed by the fixed effects. Nevertheless, we also document that our estimates of β are stable after the inclusion of a broad range of non-parametric controls.

Estimates of Equation 12 are reported in Table 1. CPP mismatch significantly inhibits the international flow of technology, both when we combine the intensive and extensive margins (column 1) and when we estimate the extensive and intensive margins effects separately (columns 2-3) The estimate from column 3 implies that CPP mismatch inhibits 30% of international technology transfer for the median in-sample level of CPP mismatch. Even before restricting attention to frontier-origin countries, inappropriateness is a major barrier to international technology diffusion.

Sensitivity: Measurement. We next probe the sensitivity of the baseline estimates; these estimates are reported in Table A5. Column 1 reproduces our baseline estimates for reference. In column 2 , we show our results are stable using the Jaccard (1900) mismatch metric (Equation 10). In column 3, we show the same using the "broad" definition of CPP mismatch that includes eradications. In Appendix B.1, we discuss how we can use the CABI data to identify possible species invasions in recent history and show the stability of our results to excluding all invasive CPPs or CPPs with high invasion potential.

[22]The exact interpretation of these effects is described in Proposition 1 and its proof.

Table 2: CPP Mismatch with Frontier Countries and Technology Transfer

	(1)	(2)	(3)	(4)
	Dependent Variable is (asinh) Biotech Transfers			
Frontier defined as:	United States	Top Variety Developer	Top 2 Variety Developers	Top 3 Variety Developers
CPP Mismatch (0-1)	-0.0571**	-0.0453**	-0.0330	-0.0207
	(0.0216)	(0.0215)	(0.0199)	(0.0196)
CPP Mismatch (0-1) x Frontier (0/1)	-0.392***	-1.237***	-1.076***	-1.076***
	(0.0313)	(0.290)	(0.249)	(0.249)
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	0.439	0.443	0.444	0.444

Notes: The unit of observation is a crop-origin-destination. The definition of a leader in each secification is noted at the top of each column and the dependent variable is noted in the panel heading. Standard errors are double-clustered by origin and destination and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Sensitivity: Additional Controls. We then explore whether the results are sensitive to the inclusion of a series of control variables. As a result of the included fixed effects, any control variable must vary at the country-pair-by-crop level. Features like geographic or cultural distance between countries are fully absorbed by the country pair fixed effects, as are any crop-level conditions at either the origin or destination. One variable that varies across crops and country pairs is crop-specific trade. In column 4 of Table A5, we control for an indicator that equals one if countries ℓ and ℓ' engage in bilateral final good trade for crop k and the estimate is similar. While distance between country pairs is fully absorbed, another possibility is that the impact of distance differs across crops in a way that is correlated with CPP mismatch. In column 5, we control for (log of) the geographic distance between all country pairs interacted with a full set of crop fixed effects, allowing the effect of distance to vary flexibly across crops. In columns 6 and 7, we exclude from the sample origin-destination pairs within 1000km or 2000km of each other respectively. Again, the estimates are very similar. A final relevant characteristic could be the difference in non-CPP crop-level environmental characteristics between the origin and destination. To investigate this idea, Appendix B.2 reports results after controlling for several non-CPP measures of ecological mismatch across crops and country-pairs. In all cases, our estimates are quantitatively very similar.

3.3 Results: Inappropriateness of the Frontier Matters Most

While estimates from the previous section capture the average relationship between CPP mismatch and technology transfer across all countries and crops, the next question we investigate is whether inappropriateness of frontier countries has a disproportionate effect on technology transfer.

Intuitively, having a high CPP mismatch with the US for corn, a crop in which it dominates global R&D, could have a larger impact on technology diffusion than CPP mismatch with a country less active in corn research. In the model, Proposition 1 formalizes that this prediction could be true if there are scale effects in the local research spillover.

To empirically investigate this quesiton, we estimate versions of the following augmented version of (12) that parameterizes heterogeneity in the effect of CPP mismatch:

$$y_{k,\ell',\ell} = \beta^{NF} \cdot \text{CPPMismatch}_{k,\ell',\ell} + \beta^{F} \cdot F_{k,\ell'} \cdot \text{CPPMismatch}_{k,\ell',\ell} + \chi_{\ell,\ell'} + \chi_{k,\ell} + \chi_{k,\ell'} + \varepsilon_{k,\ell,\ell'} \quad (13)$$

where $F_{k,\ell'}$ is an indicator variable that equals one for the countries ℓ' that we identify as the frontier countries for crop k. We have two strategies for defining $F_{k,\ell'}$. The first is to treat the US as the frontier for all crops, or set $F_{k,\ell'} = \mathbb{I}[\ell' = \text{US}]$. This method is motivated by the United States' pre-eminence in modern agricultural research.[23] 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 $F_{k,\ell'} = \mathbb{I}[\ell' \in T_N(k)]$, and is parameterized by the list length N. In this specification, β^F captures the difference in the marginal effect of inappropriateness on technology diffusion when the origin country is a leader in biotechnology development.

Estimates of Equation 13 are reported in Table 2. The dependent variable is the inverse hyperbolic sine transformation of the number of variety transfers; analogous estimates of the intensive and extensive margin effects, reported separately, are presented in Table A7. Our definitions of the frontier as the US, $T_1(k)$, $T_2(k)$, and $T_3(k)$ are used in columns 1-4. We find strong, significant evidence that $\beta^F < 0$ across all specifications. For example, in columns 3-4, the marginal effect of CPP distance on technology diffusion is roughly thirty times larger for frontier origin markets and statistically indistinguishable from zero for non-frontier origin markets. These estimates imply that high ecological mismatch with the frontier can leave a country with little or no appropriate modern technology. Interpreted via the model, they are consistent with a large context-specific component of modern technology and local research spillovers in frontier countries.

3.4 Additional Analysis: Technology Transfer and Adoption in Africa

One limitation of our analysis so far in this Section is that we lack data on technology transfer when IP protection for varieties is absent. This has two consequences. First, the analysis has been geographically limited to countries that enforce IP protection, notably excluding large parts of Africa. Second, the analysis covers only IP-protected technologies, which may neither cover all circulated varieties nor always reflect what is available to farmers. To directly investigate this set of issues, we include two additional analyses of variety introduction and usage in Africa.

[23] The US alone 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).

Variety Introduction. In Appendix B.4, we use alternative data to study how variety introduction in sub-Saharan Africa depends on the inappropriateness of the frontier. We compile data from the Consultative Group on International Agricultural Research (CGIAR) Diffusion and Impact of Improved Varieties in Africa (DIIVA) project cataloging improved crop varieties for 28 countries in sub-Saharan Africa and across 19 crops since 1960. Crucially, these data do not rely on IP protection. We find that country-crop combinations more mismatched with the frontier (i.e., the highest variety-producing countries in our main analysis) have fewer variety introductions, conditional on crop and country fixed effects.

Variety Adoption. In Appendix B.5, we study how inappropriateness affects technology adoption on smallholder farms in sub-Saharan Africa. Smallholder farms have received substantial attention for the low penetration of agricultural technology despite ostensible benefits (see, e.g., Suri, 2011; Duflo et al., 2011). We measure the use of improved technologies using data from the latest geo-coded round of all Living Standard Measurement Survey (LSMS) Integrated Surveys of Agriculture (ISA). These are detailed surveys on all facets of agricultural production, including technology use, collected by the World Bank in collaboration with the statistical agencies of eight countries: Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda.

Our outcome variable is a crop-by-farm indicator for the use of improved seeds (i.e., not locally bred varieties), as reported in the LSMS-ISA survey. One shortcoming of this measure is that self-reported data on improved seed use are not always accurate. For example, Kosmowski et al. (2019) compare survey evidence to DNA re-analysis in Ethiopia and find that farmers are accurate approximately 60% of the time. Wineman et al. (2020), in a similar analysis in Tanzania, find that farmers are accurate approximately 70% of the time. Our assumption is that this measurement error is not systematically correlated with CPP mismatch across cross-country pairs conditional on crop and country fixed effects.

We find that, in country-crop pairs more mismatched with the frontier, individual smallholder farmers are less likely to use improved seeds (Table A8). The baseline estimates imply that improved seed use by the median farmer in our sample would be 14% more prevalent absent inappropriateness, relative to an in-sample mean of 17.9%. The coefficient estimates are similar after including state fixed effects or a quadratic polynomial in farm latitude and longitude to control more flexibly for the local geography and after weighting by farm size.

These estimates indicate that inappropriateness contributes toward low improved input use on some of the world's least productive small farms. Through the lens of our model, in which endogenous innovation responds to demand for inputs, they further suggest a reason why research and marketing investment from global biotechnology firms has not materialized in sub-Saharan Africa (Access to Seeds Foundation, 2019).

4. Results: Inappropriateness and Production

We now study how mismatch with frontier innovating countries affects global production. We find that CPP mismatch with the frontier substantially reduces output at the country-by-crop level.

We find similar effects in a sub-national analysis of Brazil and India. We finally use two events, the Green Revolution and the recent rise of US biotechnology, to document how changes in the geography of innovation translate into changing incidence and effects of inappropriateness.

4.1 Data and Measurement

Agricultural Production. We compile data on crop output, trade, and prices from the UN Food and Agriculture Organization statistics database (FAOSTAT). We also compile sub-national agricultural output data from the latest nationally representative agricultural census for both Brazil and India. The Brazilian data are from the 2017 round of the Censo Agropecuário and cover 49 crops. The Indian data are from the ICRSAT Database, constructed from the 2015 Agricultural census, and cover 20 states and 20 crops.

Mismatch with the Frontier. Mapping our analysis to the predictions of Proposition 2 requires taking a stand on "which inappropriateness matters" for determining a given country's production, or from where that country sources its technology. Since we lack detailed data on the country of origin for the crop-specific inputs used in each market, we instead use the two feasible strategies to measure each country's ecological mismatch with the *frontier technology producers* introduced in Section 3.2.

The main strategy is to 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:

$$\text{CPPMismatchFrontier}^{\text{Est}}_{k,\ell} = \sum_{\ell' \in T(k)} \left(\text{Share Varieties}^{\text{UPOV}}_{k\ell'} \right) \times \left(\text{CPP Mismatch}_{k,\ell,\ell'} \right) \tag{14}$$

For our baseline results, we use $N = 2$; however, the results are very similar for alternative values for N. An advantage of this method is that it captures geographic variation in technological leadership by using international data on technology development.[24]

The second strategy is to assume that the United States produces the frontier technology for all crops and define $\text{CPPMismatchFrontier}^{\text{US}}_{k,\ell} = \text{CPPMismatch}_{k,\ell,\text{US}}$. In the model, this method is exactly correct if the United States were the sole producer of technology. In reality, nearly fifty percent of private research investment takes place in the US, representing a large share of global innovation (Fuglie, 2016). While this strategy does not capture potential variation across crops in technological leadership, it also does not rely on any cross-national comparisons of variety release intensity, which might be biased if there are differences in reporting accuracy or inclusion criteria.

These strategies for defining frontier innovators are further motivated by the results in Table 2, showing that CPP mismatch with the US or countries in $T(k)$ have a disproportionate negative effect on biotechnology diffusion. In practice, the two measures of CPP mismatch are highly correlated; in a univariate regression, the coefficient is 0.93 (0.047) and R^2 is 0.91. The underlying reason is

[24] In the model, this can be mapped to a case in which only the countries $\ell \in T(k)$ produce technology for k, productivity $\Theta_{k,\ell}$ is linearly approximated in $\delta_{k,\ell,\ell'}$ around a steady state with $\delta_{k,\ell,\ell'} \equiv 0$ for all ℓ', and $\text{ShareVarieties}_{k,\ell'}$ equals the fraction of farms that would use ℓ' technology if all technology were equally appropriate.

that our identified technological leaders, in the majority of cases, are subsets of the US, Canada, and countries in Western Europe. This foreshadows the fact that our main findings are similar using either measure.

Direct Effects of the Local Environment. In the model, the relationship between ecological mismatch and production was correctly specified conditional on measurements of the parameter $\omega_{k,\ell}$, local innate suitability for growing crop k in country ℓ (Proposition 2). To directly capture the impact of local suitability on output in our analysis, we use two measurement strategies. First, we directly measure crop-specific production as predicted by local geography from the FAO Global Agro-Ecological Zones (GAEZ) model and database (see, e.g., Costinot et al., 2016). We compute total predicted production under GAEZ's low-input, rain-fed scenario, which holds fixed background differences in input use and technology, on the land area within a country on which a given crop was grown according to a cross-section in 2000, as measured by the *EarthStat* database of Monfreda et al. (2008). While this method parsimoniously summarizes agronomic predictions of innate suitability, it is only available for 34 of our 132 crops.

Our second approach is to compile a larger set of environmental variables and then use post-double LASSO (Belloni et al., 2014) to select an appropriate set of control variables, tantamount to specifying our own crop-specific empirical models for suitability. We first construct fixed effects for the 200 "most geographically prevalent" CPPs, as determined by the number of countries in which they are present, and the 200 "most agriculturally prevalent" CPPs, as determined by the number of host species that they infect. We also construct measures of average temperature, precipitation, elevation, ruggedness, the growing season length, and soil characteristics (acidity, clay content, silt content, coarse fragment content, and water capacity) for each country. Appendix B.2 describes these data in detail. We then include all of these variables, interacted with crop fixed effects, in the LASSO control set.

4.2 Results: Inappropriateness Reduces Agricultural Output

Estimation Framework. Our main estimating equation is the empirical analog of Equation 8 in Proposition 2:

$$y_{k,\ell} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell} + \chi_\ell + \chi_k + \Omega'_{k\ell}\Gamma + \varepsilon_{k,\ell} \tag{15}$$

The outcome $y_{k,\ell}$ is average production from 2000 to 2018 in log physical units. All specifications include country and crop fixed effects (χ_ℓ, χ_k). The vector $\Omega_{k,\ell}$ includes proxies for innate suitability.

The coefficient of interest is β, which captures the effect of CPP dissimilarity from technology-producing countries on features of agricultural production. The included fixed effects capture any aggregate differences across countries (e.g., income, productivity, technology) or crops (e.g., market size, price, global innovation).[25] We also account directly for the effect of crop-level innate suitability by including various measures of crop-specific suitability, $\Omega_{k,\ell}$, described in the previous section. In Section 4.3, we will estimate a within-country variant of this empirical model which makes it possible to directly account for any crop-by-country confounders, and in Section 4.4 we will exploit

[25] A structural interpretation consistent with this is in the proof of Proposition 2.

Table 3: CPP Mismatch Reduces Agricultural Output

	(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)	-7.136***	-5.721***	-7.202***	-6.288***	-9.285***	-10.60***	-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 whch 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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

two natural experiments that shifted the research frontier to identify the impact of inappropriateness on production in a dynamic framework.

Main Estimates. Our baseline estimates of Equation 15 are reported in Table 3. In columns 1-4, CPP mismatch with the frontier is measured as mismatch with the frontier country set, $T_2(k)$. To make sure our findings are not driven by the data-driven frontier country selection, in columns 5-8 we report identical specifications in which CPP mismatch with the frontier is measured as CPP mismatch with the US for all crops. In columns 1 and 5, which include crop and country fixed effects but no additional controls, we estimate a large, negative effect of CPP mismatch with the frontier on agricultural output. The coefficient from column 5 implies that a one standard deviation increase in CPP mismatch with the research leader lowers output by 0.43 standard deviations.

The set of partial correlation plots in Figure 5 visually display the relationship between CPP mismatch with the frontier and crop-specific output for a set of large crops: corn, wheat, rice, and soybeans. For each crop, CPP mismatch substantially lowers output; the relationship does not appear driven by outlier observations or any specific part of the output distribution. These figures also show that the main result is visibly apparent in the world's most economically important crops.[26]

The remaining columns of Table 3 show the stability of these estimates under each of our control strategies for innate suitability. In columns 2 and 6, we report estimates that include the GAEZ

[26]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 A4, 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.

agronomic model-derived output estimate as a control. In columns 3 and 7, we show estimates from the post-double LASSO control strategy using the top CPP fixed effects. In columns 4 and 8, we expand the LASSO pool to include the full set of country-level geographic covariates, and their square, interacted with crop-fixed effects, to allow for crop-specific effects of each characteristic. The estimates are stable across specifications.

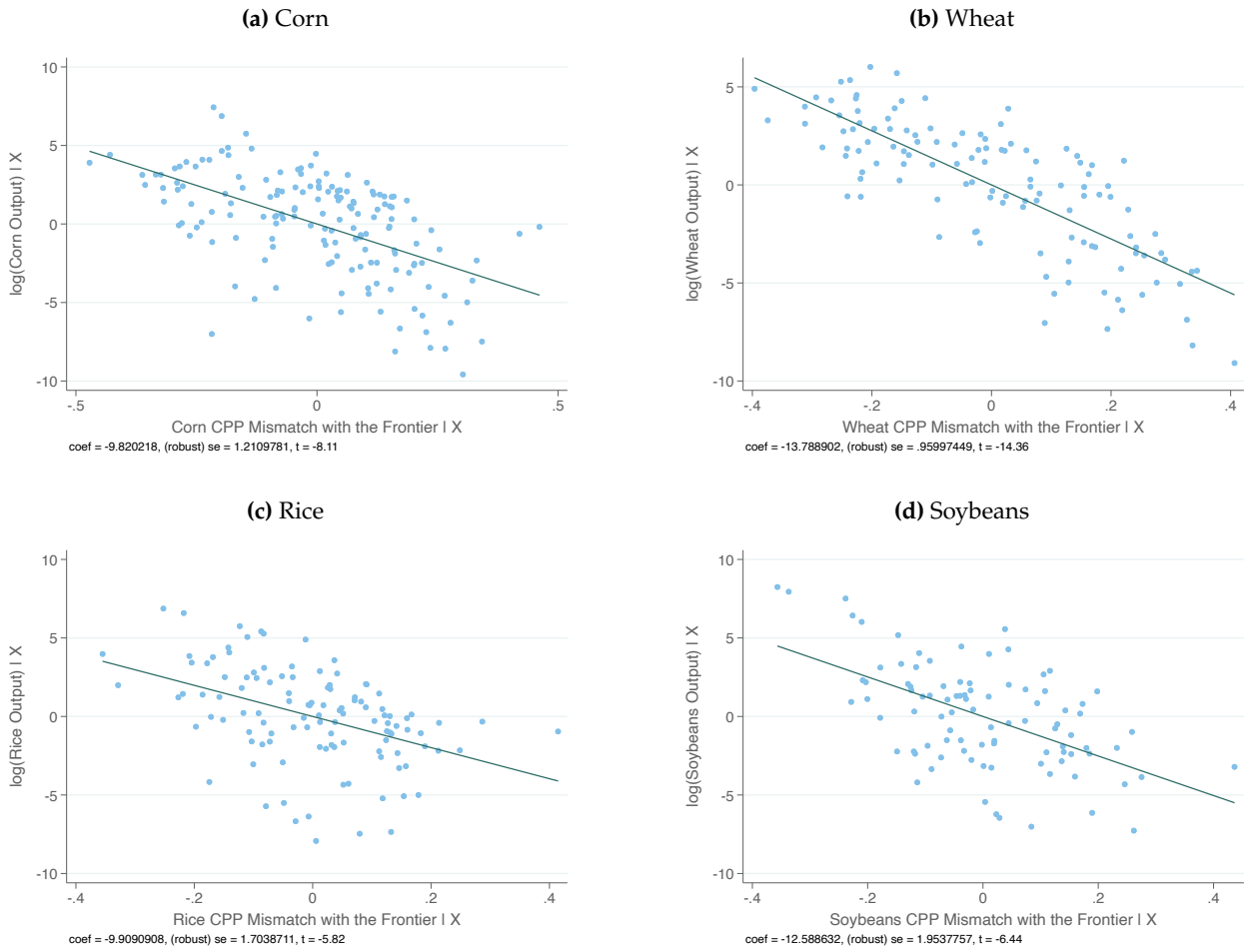
The stability of all findings after accounting for local suitability is consistent with the fact that, *ex ante*, there is no reason to expect that the locations with most innovation for a particular crop are also innately the best places for growing that crop. Thus, there is no reason to believe that being ecologically "distant" from technology producing countries is equivalent to being ecologically "bad." Indeed, the US has a long history of science and technology development to confront crop disease and the challenging pathogen environment (Olmstead and Rhode, 2008). Consistent with this history of ecological challenges in what would become a highly agriculturally productive country, existing empirical evidence suggests that variation in local land suitability plays a limited role in explaining global productivity differences (Adamopoulos and Restuccia, 2022). Our results, on the other hand, suggest that geography affects productivity, but in an indirect way. Technological progress in the frontier increases relative productivity in places with similar ecological characteristics; thus, "good geography" is determined endogenously and can change in response to shifting patterns of innovation. We directly test this dynamic prediction in Section 4.4.

Falsification Test. If our main estimates capture the impact of inappropriateness on productivity, then we would expect to find a limited or absent relationship between CPP mismatch with countries that are *not* centers of biotechnology development and productivity. To test this prediction, we re-estimate Equation 15, replacing $\text{CPPMismatchFrontier}_{k,\ell}$ with CPP mismatch with each country in the world; this generates a series of coefficient estimates $\hat{\beta}^{\ell}$, one for each country. Figure A5 reports histograms of estimates of the $\hat{\beta}^{\ell}$, both from specifications that do not include CPP mismatch with frontier as a control (A5a) as well as from specifications that do (A5b). In both cases, the coefficient on CPP mismatch with the frontier, marked with a dotted line, is in the far left part of the coefficient distribution. Estimates of the effect of CPP distance to other countries are centered around zero.

Moreover, the $\hat{\beta}^{\ell}$ are significantly negatively correlated with country-level biotechnology development measured in the UPOV database. Table A9 reports estimates of the relationship between $\hat{\beta}^{\ell}$ and both the number of varieties development in ℓ in the UPOV data (column 1) and an indicator that equals one of country ℓ enforces intellectual property protection for plant biotechnology at all (column 2). The coefficient estimates are negative and significant, suggesting that CPP mismatch has more bite on global production for precisely the countries that are more active in R&D. These findings are consistent with our main estimates capturing the causal impact of technology's inappropriateness.

Sensitivity Analysis. While Table 3 showed that the estimates were very similar after accounting for innate suitability, the key control according to the model, we also investigate the precision of the estimates after including a broader range of additional controls. As a result of the fixed effects in Equation 15, any control variable must vary at the country-by-crop level. Country-level

Figure 5: CPP Mismatch and Agricultural Output: Large Crops



Notes: Each sub-figure reports a partial correlation plot of an estimate of (15) in which we restrict the sample to a single crop: corn, wheat, rice, and soybeans in A4a - A4d 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.

characteristics like income, the human capital, physical capital, or the political environment, are absorbed by the country fixed effects. Crop-level characteristics like global demand conditions, global research effort, and physiological characteristics, are absorbed by the crop fixed effects.

The first possibility that we explore is that country-level characteristics have heterogeneous effects across crops—if these effects were correlated with CPP mismatch and production, it could bias our estimates. This could be the case, for example, if being wealthier disproportionately boosts productivity for a given crop because returns to input investment are higher, and wealthier countries tend to have lower CPP mismatch with the frontier for that crop in the data. Certain crops could also disproportionately benefit from overall specialization in agriculture or from the extent of local R&D. As an initial test of whether the results are driven by differences in crop-specific characteristics across broad regions of the world, Table A10 documents that the results are very similar including crop-

by-continent fixed effects, which allow us to focus on even more geographically precise variation. Next, Table A11 shows that results are similar after controlling for a broad spectrum of country-level characteristics, all interacted with crop fixed effects to allow their impact on production to vary systematically across crops. The controls that we include are income, openness to trade, measures of inequality, specialization in agriculture, agricultural productivity, and R&D investment.

Finally, we show that the results are not driven by non-CPP measures of geographic mismatch with the frontier, which varies at the crop-by-country level. The results are very similar after controlling directly for mismatch with the frontier in non-CPP ecological characteristics (Appendix B.2). Inappropriateness measured using non-CPP ecological characteristics also reduces output; however, this effect is independent from and smaller in magnitude than the effect of CPP distance (Table A12). The results are also not driven by differences in the extent of species invasion; the estimates are very similar after excluding all invasive species from the CPP mismatch measure (Appendix B.1).

Additional Outcomes: Trade and Price Volatility. Table A13 reports an analogous set of estimates to Table 3 with log of area harvested (instead of output) as the dependent variable. Consistent with the predictions of the Fréchet model for selection effects, we find statistically indistinguishable magnitudes compared to our main estimates for production.

Table A14 reports the impact of CPP mismatch on other features of agricultural production. First, we document that CPP mismatch with the frontier is negatively correlated with crop-specific exports (column 2), and positively (albeit insignificantly) correlated with crop-specific imports (column 3). Second, we document that CPP mismatch is positively correlated with producer price volatility. This finding indicates that the appropriateness of frontier technology might not only raise average productivity but also increase producers' ability to withstand periodic negative productivity shocks.[27] The negative relationship with producer price volatility is similar even after holding total output fixed (columns 5 and 7).

4.3 Results: Inappropriateness Reduces Agricultural Output Within Countries

We next exploit state-level information on CPP presence for Brazil and India to estimate the effects of inappropriateness at a sub-national level. Our estimating equation is:

$$y_{k,s} = \beta \cdot \text{CPPMismatchFrontier}_{k,s} + \chi_s + \chi_{k,\ell(s)} + \Omega'_{k,s}\Gamma + \varepsilon_{k,s} \tag{16}$$

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, market size, demand, and pest composition.

Our estimates of Equation 16 are displayed in Table 4, which follows the same structure as the baseline country-by-crop estimates in Table 3. We find negative and significant estimates that are

[27] For example, bad insect outbreaks; see Stone (2020) on recent locust outbreaks in East Africa.

Table 4: CPP Mismatch Reduces Agricultural Output: Sub-national 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)	-11.89***	-10.10***	-11.85***	-10.37***	-8.925***	-10.20***	-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 and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

similar in magnitude to our country-by-crop results. The coefficient estimates, if anything, increase after accounting for local suitability, either controlling for state-by-crop level FAO GAEZ predicted output (columns 2 and 6), or using the flexible post double LASSO approach (columns 3-4, 7-8). The estimates are also similar if we focus on either India or Brazil separately (Figure A6).

Together, these estimates suggest that the inappropriateness of technology shapes productivity differences not only across country-crop pairs, but across regions *within* countries for a given crop. Moreover, while we show that the findings in Section 4.2 are robust to a range of strategies to account for crop-by-country level observables, the inclusion of crop-by-country fixed effects in Table 4 fully rules out the possibility that the results are driven by unobservable characteristics that vary across country-crop pairs.

4.4 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.

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 (Pingali, 2012). 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 A15). While HYV breeding involved international collaboration, the focus of activity in certain hubs anecdotally led to technology most appropriate for primary breeding locations.[28]

We exploit the shift of innovation toward the IARCs to identify how changes in the focus of innovation affect global production. As an instrument for 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.

To validate this measure, we study its relationship with HYV adoption, as measured at the crop-by-country level by Evenson and Gollin (2003a,b). We regress the percent of area devoted to HYVs in 1980-85, a representative cross-section after the bulk of Green Revolution research was conducted, on $\text{CPPMismatchGR}_{k,\ell}$, on a sample of eight staple crops intersected with the 85 low-income countries:

$$\text{HYVAdoption}_{k,\ell,1985} = \beta \cdot \text{CPPMismatchGR}_{k,\ell} + \chi_{\ell} + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \tag{17}$$

We find that CPP mismatch with centers of Green Revolution breeding substantially reduced the adoption of HYVs (Figure 6a and Appendix Table A16)). In a falsification exercise, we estimate the relationship between HYV adoption and CPP mismatch with all other countries, and we compile these placebo coefficients. Our main estimate is in the far left tail of the coefficient distribution ($p = 0.013$), suggesting that our findings are driven by features of IARC ecology.

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

$$\Delta \log y_{k,\ell}^{80-60} = \beta \cdot \text{CPPMismatchGR}_{k,\ell} + \tau \cdot \log y_{k,\ell,1960s} + \chi_{\ell} + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \tag{18}$$

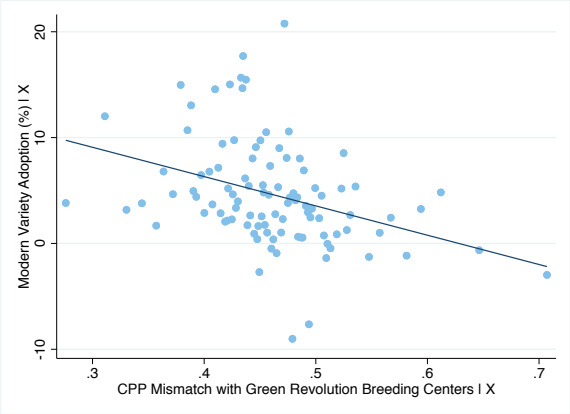
where the dependent variable is the *change* in (log of) crop-level output between the 1960s and the 1980s, and the sample includes all crop-country pairs from the HYV adoption model. This estimating equation differences out a country-by-crop fixed effect in *levels* of production, or the direct effects of time-invariant ecology and local suitability. To even more strongly account for differences in innate productivity, we control for output in the 1960s ($\log y_{k,\ell,1960s}$), which directly captures differential trends in initial output. Our hypothesis is that $\beta < 0$, or that Green Revolution technology disproportionately benefitted locations where it was most appropriate.

Figure 6b reports the partial correlation plot corresponding to Equation 18. Production substantially shifted away, in relative terms, from crop-location pairs more ecologically mismatched with the IARCs. Table A17 documents that the relationship between CPPMismatchGR and production

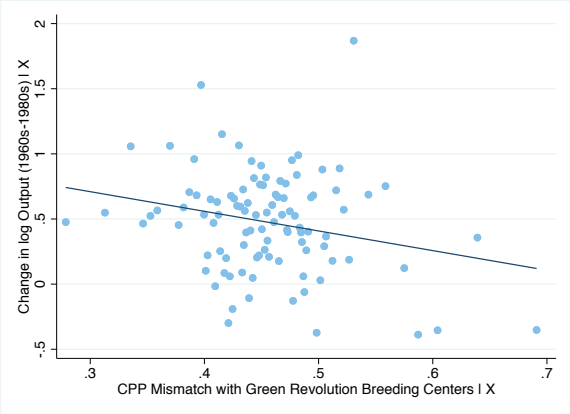
[28] Reynolds and Borlaug (2006), for example, extensively describe the challenges of coordinating breeding at the CIMMYT in Mexico with international collaborators.

Figure 6: Inappropriateness and the Impact of the Green Revolution

(a) HYV Adoption



(b) Δ log Output (1960-1980)



Notes: This figure displays binned partial correlation plots, after absorbing country and crop-by-continent fixed effects, in which the independent variable is CPPMismatchGR$_{k,\ell}$ and the dependent variable is listed at the top of each sub-figure. In Figure 6a, the dependent variable is the share of production using modern varieties in 1980 ($p = 0.006$) and in Figure 6b, it is the change in log output between the 1960s and the 1980s ($p = 0.017$). Standard errors are clustered by country and continent-crop.

growth is restricted to the period 1960-1980, the height of the Green Revolution (columns 1-3). The effect is apparent in Asia, Africa, and South America, but not in Europe, which was not an intended recipient of Green Revolution technology (columns 4-7).

Taken together, our findings illustrate how ecological mismatch shaped the impact of the Green Revolution. This finding is consistent with existing case-study evidence about how pest dissimilarities shaped the efficacy of Green-Revolution technology (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 agricultural biotechnology sector has produced a growing share of global innovation, driven in part by the advent and increased use of genetic modification. Figure A7 displays the relative growth of US patenting since 1990. The same trend for the EU is also reported, and does not show nearly as prominent an increase; while there were more agricultural patents in Europe than in the US during the 1990s, the US far outpaced Europe by the 2010s. During this period, patenting growth in US agricultural biotechnology far outpaced patenting growth in the US economy at large, coinciding with rapid growth in private capital investment (Fernandez-Cornejo and Caswell, 2006, p. 2).

We exploit this disproportionate growth of the US, relative to Europe, as a second strategy to study how changes in innovation translate, via inappropriate technology, to changes in global production. For each country-crop pair, we estimate:

$$\Delta \log y_{k,\ell}^{10-90} = \beta_1 \cdot \text{CPP Mismatch}_{k,\ell}^{US} + \beta_2 \cdot \text{CPP Mismatch}_{k,\ell}^{EU} + \gamma \cdot \log y_{k,\ell}^{1990} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \quad (19)$$

Our first hypothesis is that $\beta_1 < 0$, or that the rise in US biotech shifted production toward places ecologically similar to the US. Our second hypothesis is that $\beta_1 < \beta_2$, or that this effect is associated with the particular rise of the US and not with similarity to other high-income regions.

We find evidence of both hypotheses, across a range of regression specifications (Table A18). The effect of the US, β_1, is negative and statistically significant in all specifications. The effect of the EU, β_2, is by contrast close to zero and positive in all specifications. Moreover, 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 A8); the implied p-value from this randomization test is $p = 0.004$. 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 Table A19).

This set of results is consistent with the causal effect of R&D growth and inappropriateness driving the negative relationship between CPP mismatch with the US and output growth. Together with our analysis of the Green Revolution, these findings suggest that global productivity differences are endogenous to the evolving landscape of technology development.

5. Inappropriate Technology and Productivity: Present and Future

We finally combine our empirical estimates with the model to explore how the inappropriateness of technology shapes the distribution of global agricultural productivity. Our goal is to illustrate, in a simple framework, the quantitative magnitudes at stake due to the inappropriateness of technology. We then use our framework to study a series of counterfactual scenarios that model how inappropriateness mediates three ongoing changes in global biotechnology and the environment: modern targeting of philanthropic research, the rise of new R&D hubs in emerging markets, and the global movement of crop pests and pathogens due to climate change.

5.1 Methods

Set-up. Our empirical findings about technology transfer in Section 3 and production distortions in Section 4 suggest there are crop-specific "leaders" driving the frontier of agricultural technology. Building on this result, we introduce a special case of our model from Section 1 which embodies this logic, maps transparently to the empirical findings, and allows us to formally define counterfactual scenarios of interest.

Concretely, we specialize the model by assuming that for each crop k there is a "Frontier technology producer" $F_k \in \{1, \ldots, L\}$. In the Frontier, general research is inelastically supplied at level $\bar{A}_k > 0$, own-CPP research at level $\bar{B} > 0$, and foreign-CPP research at level $\bar{B}e^{-\hat{\tau}}$ for some $\hat{\tau} > 0$.[29] These assumptions encode a fixed knowledge gap in productivity units for each crop, to match our

[29]Formally, in the frontier countries, we set $B_0 = \bar{B}^{-1}$ and take a limit of $\phi \to \infty$ and $\tau \to \infty$ such that $\frac{\tau(\bar{B})}{1+\phi} \to \hat{\tau} > 0$. In other countries, we set $B_0 \to \infty$ so no research is performed.

empirical strategy in Section 4. They abstract from the endogeneity of the magnitude of knowledge gaps in response to incentives, a topic about which we have little information in the data.

We close the model by specifying the demand system. We assume that there is a representative global consumer with payoffs $u(M, C)$ defined over the numeraire good M ("money") and a bundle C of the agricultural goods.[30] That bundle is a constant elasticity of substitution (CES) bundle of crop-level consumption C_k, or

$$C = \left(\sum_{k=1}^{K} \kappa_k^{\frac{1}{\varepsilon}} C_k^{1-\frac{1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{20}$$

for some normalization constants $(\kappa_k)_{k=1}^K$ and between-crop elasticity of substitution $\varepsilon > 0$.[31] The representative consumer can purchase each crop k at a global price p_k, in terms of the numeraire. The induced demand curves are

$$\log p_k - \log p = \frac{1}{\varepsilon}(\log \kappa_k + \log C - \log C_k) \tag{21}$$

where p is the (CES) price index for all crops. Our model with aggregate global demand abstracts from trade and trade frictions, which may indirectly shape the consequences of inappropriate technology via prices. Given the large panel of crops and countries in our analysis, systematically identifying a demand system for each country and full set of crop-by-country-pair trade frictions is beyond the scope of our analysis. Accounting for these trade patterns would be important for measuring the welfare consequences of inappropriateness. We instead focus on how inappropriateness affects global agricultural productivity and productivity gaps. The extent of these gaps is an ongoing puzzle and the focus of a large body of work (see, e.g., Gollin et al., 2014).

We finally allow each country to have amount ζ_ℓ of agricultural land, which in Section 1 was normalized to one. Introducing these differences in scale has no effect on the model interpretation of our regression estimate from Section 4, as they would be absorbed by the country fixed effect.

From Theory to Regression. We now specialize the key model predictions about production and productivity (Proposition 2) to this case of the model. Substituting the model-derived form for fixed effects into Equation 8, we derive the regression equation[32]

$$\log \frac{Y_{k,\ell}}{\zeta_\ell} = -\eta(1-\alpha)\hat{\tau}\, \delta_{k,\ell,F_k} + \eta \log \omega_{k,\ell} + (\eta - 1) \log \hat{p}_k - (\eta - 1) \log \hat{\Xi}_\ell + \eta \left(\alpha \bar{A}_k + (1-\alpha)\bar{B} \right) \tag{22}$$

where δ_{k,ℓ,F_k} is CPP mismatch with the crop-specific frontier, $\log \hat{p}_k = \log p_k - \log p$ is the price deviation from the overall crop index, and $\log \hat{\Xi}_\ell = \log \Xi_\ell - \log p$ is location-specific productivity deflated by the same index. As derived in Appendix A, Ξ_ℓ is the expected revenue per unit of optimally allocated land in the model. Deflating by the price p is natural because it keeps constant

[30] 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.

[31] In the calibration, we set the constants κ_k so that, at the observed equilibrium, $p_k \equiv 1$ for all crops k.

[32] We furthermore assume that γ, landowners' profit share, is close to one, so the elasticity of choices to prices is $\eta/\gamma \approx \eta$.

the representative consumer's overall demand for agricultural products.[33] In this version of the model with a single crop-specific frontier, the productivity index $\hat{\Xi}_\ell$, up to irrelevant constants that depend on fixed parameters γ and η, is:

$$\log \Xi_\ell = \alpha \log \bar{A}_k + (1-\alpha) \log \bar{B} + \frac{1}{\eta} \log \left(\sum_{k=1}^{K} \hat{p}_k^{\eta} \omega_{k,\ell}^{\eta} e^{-\eta(1-\alpha)\hat{\tau}\delta_{k,\ell,F_k}} \right) \tag{23}$$

Improvements in frontier technology, or higher $\bar{A}_k$ and $\bar{B}$, benefit all crop-country pairs. But these benefits are reduced if ecological distance to the frontier, δ_{k,ℓ,F_k}, is high.

Before turning to the calibration, we make three remarks about how we will map the model equations (Equations 21, 22, and 23) to the data. The first concerns the model interpretation of our estimated elasticity of production to CPP mismatch from Section 4 (β). Comparing the empirical regression model (Equation 15) to Equation 22, we observe that $\beta = -\eta(1-\alpha)\hat{\tau}$. In words, the empirically estimated coefficient of CPP mismatch on production is the product of three terms: the elasticity of output to productivity η, the relative importance of CPP-specific technology $1-\alpha$, and the extent of knowledge spillovers $\hat{\tau}$. The second two forces need not be separately identified to quantify productivity effects using Equation 23. However, separating the first force from the latter two is important to identify the marginal effect of CPP mismatch on productivity.

The second concerns innate productivity $\omega_{k,\ell}$. When data on agricultural production are mapped exactly to Equation 22, $\omega_{k,\ell}$ is a residual. Differences in $\omega_{k,\ell}$ absorb any differences in innate suitability or in the availability of other inputs that affect productivity independently from ecological mismatch. In this section's quantitative analysis, when we vary the intensity or character of the inappropriate-technology mechanism, we treat these other determinants of productivity as fixed.[34]

The third concerns price effects and the elasticity of demand ε. Changing global prices create an equilibrium interaction between different countries' planting and therefore mediate the overall effects of technology on productivity. For example, if a studied counterfactual scenario greatly increases technological quality for one crop in excess of other crops, the price of that crop may go down; this will mute the effect on revenue productivity.

Calibration. Our calibration is summarized in Table 5. First, following the first remark above, we calibrate the supply elasticity as $\eta = 2.46$ from Costinot et al. (2016), who study productivity changes and re-allocation in global agricultural production using the Fréchet discrete choice model.[35] Combining this estimate with our baseline estimate of $\beta = -7.14$ (Table 3, column 1) yields an

[33] This demand for agricultural products is determined by the concavity of u. It is easy to verify that, if we were to specify a functional form for u, we could solve for p after solving for equilibrium normalized productivity $\hat{\Xi}_\ell$ in each country, since the level of p does not affect producers' specialization decisions.

[34] The micro-foundation of our baseline model in an expanded environment with multiple input choices in Appendix A.5 clarifies how holding fixed $\omega_{k,\ell}$ does accomodate changing *utilization* of such inputs across counterfactuals, but not changes in their prices. In Section 4 we showed that the impact of CPP mismatch on production was similar after using a set of strategies to control for innate suitability, indicating that differences in innate suitability do not seem to bias or mediate the effect of inappropriateness on production.

[35] These authors estimate, in a nutshell, is the shock heterogeneity required to explain the relationship between agronomically measured productivity (from the FAO-GAEZ model) and observed planting patterns at the plot level (about 50-square-kilometer-size) in the modern world.

Table 5: Model Parameters and Data for Estimation

Name	Estimate	Specification/Source	Definition
β	-7.14	Equation 15	Effect of CPPMismatchFrontier on output
η	2.46	Costinot et al. (2016)	Elasticity of supply to productivity
ε	2.82	Costinot et al. (2016)	Elasticity of substitution between crops
$\pi_{k,\ell}$	—	FAOSTAT Database	Planted area for each crop in each country
Ξ_ℓ, ζ_ℓ	—	Fuglie (2012, 2015)	Revenue productivity by country

estimate of $(1-\alpha)\hat{\tau} = 2.90$, in units of percent productivity loss per basis point of CPP mismatch.

Second, conditional on η, the crop-by-location productivity $\omega_{k,\ell}$ is identified up to scale from data on relative area by crop, $\pi_{k,\ell}$.[36] Mirroring our analysis in Section 4, 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, 2015), 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), $\varepsilon = 2.82$.

5.2 The Productivity Effects of Inappropriateness

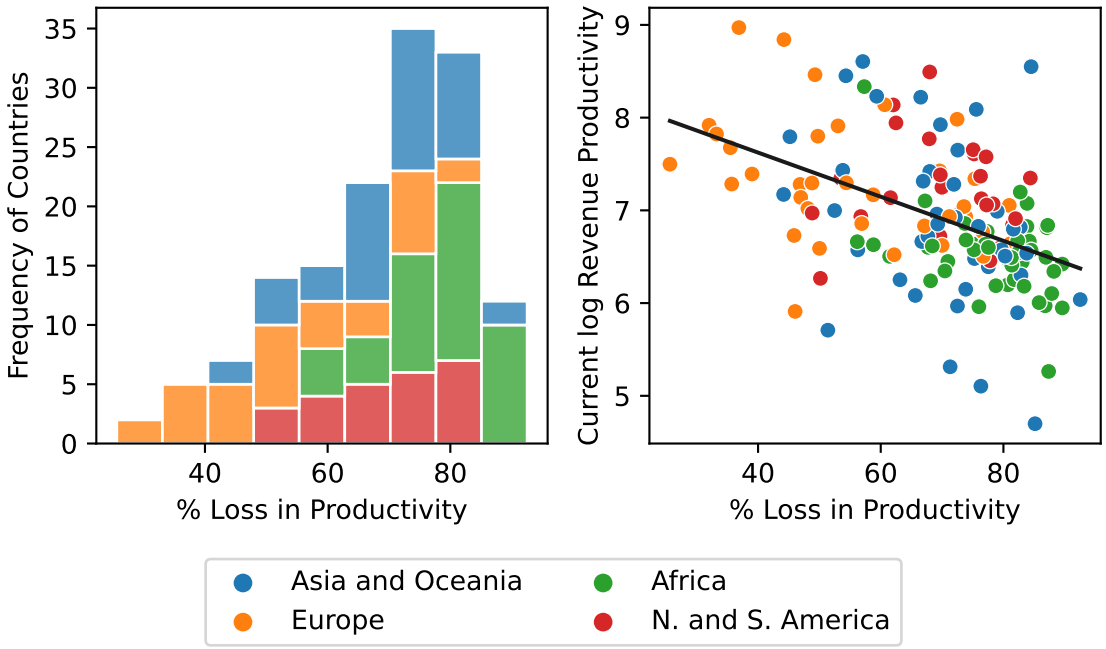
We first define and study a counterfactual in which "inappropriateness is removed." Specifically, we consider a scenario in which non-local CPP research is subsidized to reach level $\bar{B} > \bar{B}\exp(-\hat{\tau})$ in all frontier countries. One possible story underlying this scenario is that an external donor provides large enough agricultural research subsidies in frontier countries to massively redirect frontier research and overcome the lack of knowledge about non-frontier-country CPP threats. One effect, in the language of the Introduction's motivating example, is that frontier research into the Maize Stalk Borer catches up to frontier research on the "Billion Dollar Bug," the Corn Rootworm. We interpret this scenario as a benchmark for measuring the total effect of the "inappropriate technology bias" on global productivity, and not as a clearly optimal intervention under a specific welfare metric.

Using the model, we estimate the general-equilibrium effects of this change after taking into account endogenous planting patterns and price changes. We summarize our findings in two statistics: the productivity change on the world's average acre and the percent change in the 75-25 percentile gap (inter-quartile range) of the global log revenue productivity distribution. We report both findings in terms of the change from the counterfactual world without inappropriateness to the observed world with inappropriateness. We calculate standard errors for these statistics using the delta method, accounting for uncertainty in our estimate of the regression coefficient β.

We find that inappropriateness reduces global productivity by 57.7% (SE: 4.85%) and explains 15.1% (SE: 0.42%) of global disparities, as captured by the IQR. Figure 7 visualizes the distributional

[36] More precisely, $\pi_{k,\ell}$ is the area devoted to crop k in country ℓ divided by the total area devoted to all crops under study in country ℓ. Thus, by construction, the fractions add to one.

Figure 7: Causal Effects of Inappropriateness, by Country



Notes: 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.

implications of our findings. The left panel 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 conveys that the countries with the highest predicted loss from inappropriateness are the least productive today.[37]

These results, taken together, highlight the inequality created by the interaction of ecological heterogeneity with concentrated innovation. Neglected agricultural ecosystems are disproportionately located in unproductive parts of the world, which are kept unproductive due to an absence of appropriate technology or incentives to develop it.

Sensitivity to Calibrated Parameters. Our empirical analysis is focused on accurately estimating β, the effect of CPP mismatch on output. Our calibration also relies on estimates of the elasticity of supply to productivity (η) and the price elasticity of demand (ε), both obtained from existing work. To explore sensitivity of our findings, we identify maximum and minimum plausible estimates of each parameter from the literature and re-produce the counterfactual estimates using these alternative parameter values (Figure A10).[38] Decreasing the extent of unobserved heterogeneity (decreasing η)

[37]Estimated as a linear regression, this relationship is statistically significant with a t statistic of -6.22. Some, but not all, of this effect is spanned by the cross-continent variation highlighted above. Replicating the same regression model with continent fixed effects gives a coefficient of -0.019 (SE: 0.005), with a t-statistic of -3.81.

[38]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

amplifies the effects of inappropriateness by increasing our calibrated effect of CPP mismatch on productivity. Nonetheless, even our conservative choice of $\eta = 2.86$ results in an average loss of 52.4%. Changing the price elasticity does not affect our finding for average losses, although it does change the exact distributional incidence. This suggests that indirect effects of inappropriateness via relative crop prices and reallocation wash out on average across countries.

Inappropriateness Due to Other Ecological Differences. Our main results focus on CPP mismatch as a key shifter of technology diffusion and inappropriateness. However, as highlighted in Section 2.3, 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. Appendix B.2 describes our measurement of non-CPP, agro-climatic characteristics and Figure A11 visualizes the impact of removing inappropriateness in the form of this broader set of geographic and ecological features, in addition to CPP mismatch. Incorporating these additional dimensions of potential inappropriateness, as we measure them, increases our estimate of the losses due to inappropriateness to 68.2%, and increases the effect on disparities in productivity to 16.3%.

The Productivity Effects of Reallocating Research. In our baseline counterfactual scenario, total research investment in the frontier may considerably increase—the imagined subsidies equalize research focused on neglected threats with research focused on threats in the frontier. An alternative set of scenarios, which embody the same idea of "research equality" without necessarily increasing total research costs, are the following: either taxing or subsidizing all CPP research to reach level $\bar{B}\exp(-(1-\omega)\hat{\tau})$, for some $\omega \in [0,1]$. When $\omega = 1$, this is the counterfactual studied above. When $\omega = 0.58$, frontier CPP research is taxed such that the CPP mismatch between all crop-by-country-pairs equals the median in-sample mismatch, $\text{med}[\delta_{k,\ell',\ell}] = 0.42$. Figure A9 summarizes our findings. For all ω, equalizing inappropriateness reduces disparities by exactly 15.1%. This is a consequence of constant returns to scale in the model. The average productivity effect is increasing in ω and becomes positive when $\omega > 0.70$, above the point at which CPP mismatch is brought to the median value everywhere but well below the point at which all CPP research is brought to the level of the frontier.

5.3 Three Ongoing Changes in Biotechnology and the Environment

Next, we turn to a series of counterfactual analyses that capture real-world policy decisions or trends in global biotechnology.

5.3.1 Research Targeting in a "Second Green Revolution"

In the face of persistent global hunger and looming threats including climate change, there are renewed calls among governments and philanthropists for a "Second Green Revolution." Bill Gates, speaking at the World Food Prize Symposium in 2009, averred that:

literature. For the maximum plausible value, we add the difference between the Sotelo (2020) estimate and our baseline estimate of η.

Table 6: Inappropriateness-Minimizing Centers for Modern Agricultural Innovation

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Crop	Sites Chosen to Minimize Global Inappropriateness				Sites Chosen to Minimize Inappropriateness in Countries with Below Median Productivity			
	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 productivity for each crop. All estimates rely on the full model with non-linear adjustments and price responses.

> [The Green Revolution] was one of the great achievements of the 20th century. But it didn't go far enough. [...] The charge is clear—we have to develop crops that can grow in a drought; that can survive in a flood; that can resist pests and disease (Gates, 2009).

In the same speech, he especially emphasized the importance of targeting research toward neglected food systems in Africa.

Our empirical analysis of the historical ("First") Green Revolution suggested that productivity benefits were mediated by the location of the coordinating research institutes (see Section 4.4). By implication, the geographic focus of future coordinated breeding efforts in a "Second Green Revolution" could critically shape its aggregate effects. When deciding where to locate breeding efforts, a philanthropic or government organization would likely weigh two forces. The first is the cost of conducting research in a location, which may vary due to differences in breeding infrastructure, human capital, etc. While these differences in cost are incorporated in our theoretical model, exploring their quantitative impact is beyond the scope of this paper. The second force is the potential spillover benefits of targeting research in a location. On this front, our analysis provides a potential way to directly quantify these benefits which, while not being the full story, are a key ingredient in the research targeting decision making process.

Therefore, we use our model to ask: if public sector or philanthropic organizations were to design a "Second Green Revolution," where should they locate the main research centers in order to generate benefits that could potentially be shared as widely as possible? Concretely, for each of the eight Green Revolution crops, we calculate the counterfactual (general-equilibrium) productivity benefit of moving the "Frontier" to each country in the world. We then identify which new Frontier choices would have the largest effect on global productivity and on productivity in initially below-median-productivity countries, the main focus of philanthropic attention.

We report our results in Table 6. Our findings 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 results also suggest potentially large opportunities for large 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.

5.3.2 The Rise of New Technology Leaders

One of the most dramatic transformations to global innovation in the coming decades could be the expected rise of large emerging economies as hubs of R&D. In particular, the "BRIC" countries—Brazil, Russia, India, and China—are expected to become major players in global biotechnology research, and their growth in research output has already begun. Figure A12 displays the number of patented agricultural technologies in the US and in the BRIC countries over time, relative to the period 1990-1995. While the *level* of innovation in the US is higher, agricultural innovation is growing substantially faster in the BRIC countries.

What might the impact in this shift in the center of global research be on global productivity? The prominence of India and China in Table 6 hinted that such a shift in international focus may boost global productivity; moreover, several anecdotes suggest that BRIC-nation policymakers have recognized the associated business opportunities from investment in agricultural R&D and marketing it around the world. As one example, the Brazilian Agricultural Research Corporation (EMBRAPA), a state-owned agricultural research organization, has a long-standing cooperation with several African countries based on the premise of their ecological similarity.[39]

To operationalize a "Rise of BRIC" scenario in our model, we first calculate the CPP mismatch of every country-crop pair with the BRIC research frontier as:

$$\text{CPPMismatchFrontier}_{k,\ell}^{\text{BRIC}} = \sum_{\ell' \in \text{BRIC}} \frac{\pi_{\ell',k}}{\sum_{\ell'' \in \text{BRIC}} \pi_{\ell'',k}} \times \text{CPPMismatch}_{k,\ell,\ell'} \tag{24}$$

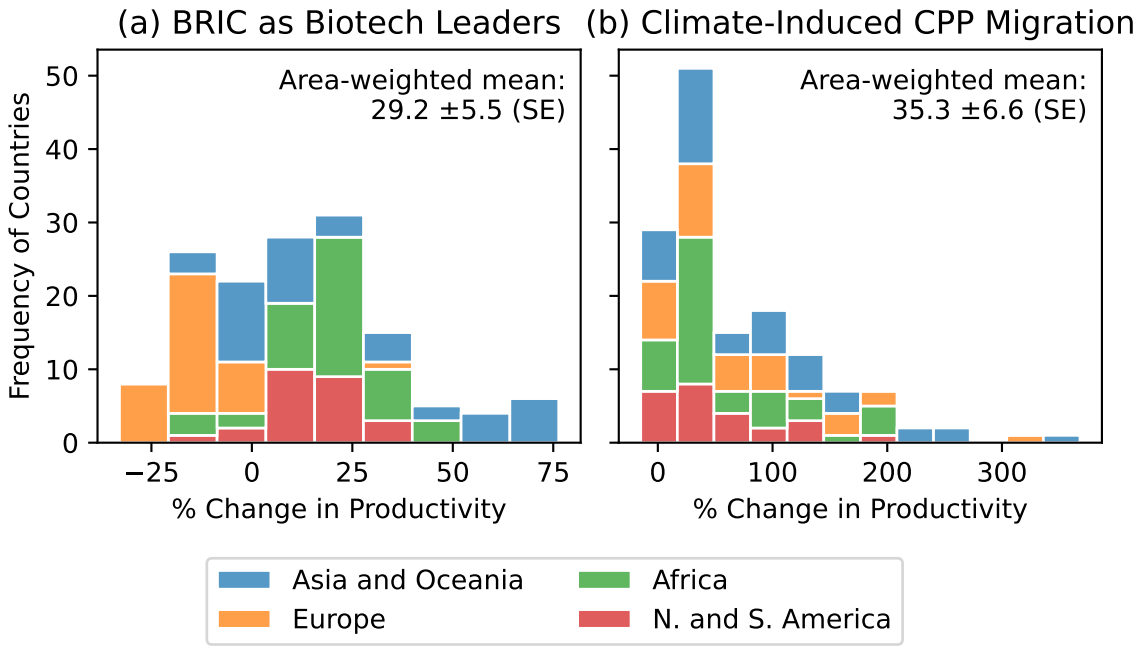
In words, we estimate the inappropriateness of BRIC ecology for each crop, weighting by area $\pi_{k,\ell}$.[40] We then consider the effects of moving the frontier such that $\delta_{k,\ell,F_k} = \text{CPPMismatchFrontier}_{k,\ell}^{\text{BRIC}}$.

Panel (a) of Figure 8 summarizes our findings in a continent-coded histogram of productivity changes. The average effect is a 29.2% productivity boost, 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, including several countries in Europe and Asia, which benefit from their ecological similarity to the current technological leaders. From the perspective of the developing world, a shift of innovation investment to the BRIC nations may be a partial, if incomplete, substitute for encouraging local technological development or for targeted investment by Western philanthropies.

[39] See here: https://www.embrapa.br/en/cooperacao-tecnica/m-boss.

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

Figure 8: Counterfactuals: Rise of BRIC and Climate-Induced CPP Migration



Notes: Each graph is a cross-country histogram of productivity changes, across countries. The left scenario corresponds to a shift of biotechnological leadership to Brazil, Russia, India, and China (Section 5.3.2) and the right scenario corresponds to a poleward migration of CPPs induced by climate change (Section 5.3.3).

5.3.3 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.[41] This could change the relevant "geography of innovation" by shifting the relevant set of CPP threats and hence the focus of technological progress in each country, even if the identity of innovating countries remains fixed.

While the rising temperatures are likely to be detrimental to agricultural production in much of the world (e.g., Lobell et al., 2008; Hertel et al., 2010), our framework highlights how the response of technology could either mitigate or exacerbate the distributional impacts of climate change. If CPP range shifts increase the ecological similarity between a given country and the Frontier, then it might be able to more effectively make use of modern technology developed in the new equilibrium. However, CPP movement could also reduce the CPP overlap across countries if, for example, the US inherits several unique CPPs from Central America (or Europe from North Africa), reducing their ecological similarity to other large parts of the world. The pattern of both ecological change and

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

technological leadership determines how innovation might shape the global productivity impacts of environmental change.

To investigate the impact of climate change on the global appropriateness of frontier technology, we extrapolate the estimates in Bebber et al. (2013) of poleward CPP movement to date into the future, using projected changes in global temperature due to climate change between the present and 2100.[42] We then use these data to construct $\text{CPPDistFrontier}_{k,\ell}^{CC}$ based on ecological dissimilarity to the modern set of frontier innovators, and re-calculate productivity as in the previous counterfactuals.

Panel (b) of Figure 8 shows that we find an overall positive effect, which is relatively evenly spread across space. Our analysis therefore highlights that increasing ecological similarity may provide a partially offsetting force to the (here, unmodeled) direct negative effects of ecological change, insofar as it coordinates the global research system around a more common set of productivity threats. This dynamic in agricultural innovation, and in climate-induced innovation more broadly, is an important topic for further research.

6. Conclusion

We investigate a long-standing hypothesis that frontier technologies' endogenous appropriateness for the high-income countries that develop them shapes global patterns of technology diffusion and productivity. Our empirical focus is global agriculture. We develop a new measure of the potential inappropriateness of crop-specific technology based on the mismatch in crop pest and pathogen (CPP) environments across crops and locations. We first show that technology development is concentrated in a small set of countries and focused on local pest and pathogen threats. We next show that environmental mismatch is a substantial barrier to the international diffusion of crop-specific technology. We finally show that countries shift production away from crops that have higher environmental mismatch with research-intensive countries. Technological progress in the frontier, far from diffusing broadly and evenly around the world, underlies global inequality.

Combining our estimates with a model of global agricultural production, we estimate that inappropriateness as captured by CPP mismatch reduces global agricultural productivity by 42%, and increases global disparities in agricultural productivity by 15%. Substantial ecological differences around the world, and innovators' neglect of ecosystem threats in low-income areas, sustains large disparities in productivity.

However, by the same token, changes in the geography of innovation can substantially alter patterns of technology adoption and productivity around the world. We show that the impact of the Green Revolution was shaped by ecological mismatch with the key breeding centers and that the rise of modern US biotechnology has disproportionately benefitted regions with lower ecological mismatch with the US. We also show how future changes in the centers of innovation and

[42]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.

in ecology, including the growth of R&D investment in large emerging markets, could have similarly large but unequal global productivity effects, as production evolves endogenously in response to the changing global appropriateness of frontier technology. Exploration of these trends, which will define agriculture and technology in the coming century, as well as policy design focused on seeding appropriate technology development around the world, are important areas for future research.

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

Contents

A. Omitted Proofs and Derivations

We first derive lemmas that assist in proving the main result (A.1). We then prove Proposition 1 (A.2) and 2 (A.3). We then micro-found our assumed pricing via monopoly pricing with varying conduct (A.4), describe a mapping between the baseline model and an extension with multiple chosen inputs (A.5), describe the relationship between private and social incentives in the model (A.6), and describe an alternative model with copycat inventors (A.7).

A.1 Supplementary Lemmas

Lemma 1. *The profit of farmer i, if they choose crop-technology (k, ℓ') and have idiosyncratic productivity draw $\varepsilon_{k,\ell',i}$, is*

$$\Pi_{k,\ell',i} = \gamma \left(\frac{1-\gamma}{q_{k,\ell',\ell}} \right)^{\frac{1-\gamma}{\gamma}} p_k^{\frac{1}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i} \tag{25}$$

Moreover, farmers' crop and technology choice solves

$$\max_{k,\ell'} \left\{ p_k^{\frac{1}{\gamma}} q_{k,\ell',\ell}^{-\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i} \right\} \tag{26}$$

Proof. Farmers solve the following profit maximzation problem for their input choice:

$$\Pi_{k,\ell',i} = \max_{X_{k,\ell',\ell}} \left\{ p_k (X_{k,\ell',i})^{1-\gamma} (\theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i})^{\gamma} - q_{k,\ell',\ell} X_{k,\ell',\ell} \right\} \tag{27}$$

This is a strictly concave problem. The first-order condition is

$$0 = (1-\gamma) p_k (\theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i})^{\gamma} (X_{k,\ell',i})^{-\gamma} - q_{k,\ell',\ell} \tag{28}$$

Rearranging, $X_{k,\ell' i} = (1-\gamma)^{\frac{1}{\gamma}} q_{k,\ell',\ell}^{-\frac{1}{\gamma}} p_k^{\frac{1}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i}$. Substituting this into Equation 27,

$$\Pi_{k,\ell',i} = \gamma p_k^{\frac{1}{\gamma}} \left(\frac{1-\gamma}{q_{k,\ell',\ell}} \right)^{\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i} \tag{29}$$

To derive Equation 26, we observe that the farmer i solves $\max_{k,\ell'} \{\Pi_{k,\ell',i}\}$, and observe that the constant $\gamma(1-\gamma)^{(1-\gamma)/\gamma}$ is irrelevant to this program.

□

Lemma 2. *The measure of farmers planting crop k with technology ℓ' in country ℓ is given by*

$$\pi_{k,\ell',\ell} = \frac{p_k^{\frac{\eta}{\gamma}} q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell}^{\eta} \omega_{k,\ell}^{\eta}}{\sum_{k'',\ell''} p_{k'}^{\frac{\eta}{\gamma}} q_{k',\ell'',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k',\ell'',\ell}^{\eta} \omega_{k',\ell}^{\eta}} \tag{30}$$

Moreover, the expected profit of farmers conditional on any (k, ℓ') choice is

$$\Xi_\ell = \gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}} \left(\sum_{k=1}^{K} \sum_{\ell'=1}^{L} p_k^{\frac{\eta}{\gamma}} q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell}^{\eta} \omega_{k,\ell}^{\eta} \right)^{\frac{1}{\eta}} \tag{31}$$

Proof. Let $u_i^* \in \{1, \ldots, K\} \times \{1, \ldots, L\}$ denote the crop-technology choice of farmer i, let

$$\nu_{k,\ell',\ell} = \gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}} p_k^{\frac{1}{\gamma}} q_{k,\ell',\ell}^{-\frac{1-\gamma}{\gamma}} \omega_{k,\ell} \theta_{k,\ell',\ell} \tag{32}$$

be the shifters of revenue for each (k, ℓ') pair in ℓ, and let $\pi_{k,\ell',\ell} = \mathbb{P}[u_i^* = (\ell', k)]$ if $i \in [\ell - 1, \ell)$. Let $F(z)$ denote the cumulative distribution function of a Fréchet random variable with scale one and shape parameter $\eta > 1$, or $F(z) = \exp(-x^{-\eta})$.

The random shock $\varepsilon_{k,\ell',i}$ is Fréchet random variable with mean one and shape $\eta > 1$, so its scale parameter is $s = (\Gamma(1 - 1/\eta))^{-1}$; thus the normalized shock $\hat{\varepsilon}_{k,\ell',i} = \frac{1}{s}\varepsilon_{k,\ell',i}$ is distributed by $F(z)$. If a farmer draws $\hat{\varepsilon}_{k,\ell',i} = z$, then that farmer chooses pair (k, ℓ') if this results in the maximum productivity among all options, or $\nu_{k,\ell',\ell} z > \nu_{k',\ell'',\ell} \hat{\varepsilon}_{k',\ell'',i}$ for all other pairs (k', ℓ''). These events are independent across all (k', ℓ''). Thus the probability of choosing (k, ℓ') is given by the probability of the event described above, conditional on each realization z, integrated over the probability distribution of z. Because of the assumed law of large numbers, this also gives $\pi_{k,\ell',\ell}$. We therefore write

$$\begin{aligned}
\pi_{k,\ell',\ell} &= \int_0^\infty \prod_{k',\ell'' \neq k,\ell'} F\left(\frac{\nu_{k,\ell',\ell}}{\nu_{k',\ell'',\ell}} z\right) \mathrm{d}F(z) \\
&= \int_0^\infty \left(\prod_{k',\ell'' \neq k,\ell'} \exp\left(-\left(\frac{\nu_{k,\ell',\ell}}{\nu_{k',\ell'',\ell}} z\right)^{-\eta} \right) \right) \eta z^{-1-\eta} \exp(-z^\eta)\, \mathrm{d}z \\
&= \int_0^\infty \eta \exp\left(-z^{-\eta} \frac{\Xi_\ell^\eta}{\nu_{k,\ell',\ell}^{-\eta}} \right) z^{-1-\eta}\, \mathrm{d}z
\end{aligned} \tag{33}$$

where we substituted the expression for $F(z)$ in the second line and simplified and defined the

productivity index

$$\Xi_\ell = \left(\sum_{k=1}^{K} \sum_{\ell'=1}^{L} \nu_{k,\ell',\ell}^{\eta} \right)^{\frac{1}{\eta}} \tag{34}$$

in the third line. After a change in variables in the integrand to $\tilde{z} = z \frac{\nu_{k,\ell',\ell}}{\Xi_\ell}$, the original integral can be re-written and simplified as

$$\begin{aligned} \pi_{k,\ell',\ell} &= \frac{\nu_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''} \nu_{k',\ell'',\ell}^{\eta}} \int_0^\infty \eta \exp\left(-\tilde{z}^{-\eta}\right) \tilde{z}^{-1-\eta} \, \mathrm{d}z \\ &= \frac{\nu_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''} \nu_{k',\ell'',\ell}^{\eta}} \int_0^\infty \mathrm{d}F(\tilde{z}) = \frac{\nu_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''} \nu_{k',\ell'',\ell}^{\eta}} \end{aligned} \tag{35}$$

Re-writing the last line with the definition of $\nu_{k,\ell',\ell}$ completes the derivation of $\pi_{k,\ell',\ell}$.

We next derive profitability of (k, ℓ') production conditional on choice. Let

$$V_i^* = \max_{k',\ell''} \left\{ \nu_{k',\ell'',\ell} \varepsilon_{k',\ell'',i} \right\} \tag{36}$$

denote the profitability of farmer i evaluated at the optimal choice. The probability that V_i^* is less than some value v, conditional on the optimal choice being (k', ℓ''), can be obtained by integrating the right-hand-side of Equation 33 up to the realization $\frac{v}{s\nu_{k',\ell'',\ell}}$, and normalizing by the probability of choosing (k', ℓ''):

$$\mathbb{P}[V_i^* \leq v \mid u_i^* = (k', \ell'')] = \frac{1}{\pi_{k,\ell',\ell}} \int_0^{\frac{v}{s\nu_{k',\ell'',\ell}}} \prod_{k',\ell'' \neq k,\ell'} F\left(\frac{\nu_{k,\ell',\ell}}{\nu_{k',\ell'',\ell}} z \right) \mathrm{d}F(z) \tag{37}$$

After the change in variables in the integrand to $\tilde{z} = z \frac{\nu_{k,\ell',\ell}}{\Xi_\ell}$,

$$\mathbb{P}[V_i^* \leq v \mid u_i^* = (k', \ell'')] = \int_0^{\frac{v}{s\Xi_\ell}} \mathrm{d}F\left(\tilde{z}\right) \tag{38}$$

which implies that V_i^*, conditional on $u_i^* = (k', \ell'')$, can be written as the product of Ξ_ℓ and a unit-mean, η-shape Fréchet random variable. Since this is invariant to k', ℓ'', this is also the unconditional distribution of V_i^*. Thus, $\mathbb{E}[V_i^* | u_i^* = (k', \ell'')] = \Xi_\ell, \forall (k', \ell'')$. This implies the desired claim, after substituting in the expression for Ξ_ℓ.

□

Lemma 3. *Each innovator's research in (k, ℓ) specific technology solves the following problem*

$$\max_{(B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}} \left\{ e^{-\rho_{\ell',\ell}} R\left((B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}; \hat{p}_k, \hat{\Xi}_\ell, \mu_{\ell'}\right) - \sum_{t\in\mathcal{T}_{k,\ell}} e^{-\tau(\hat{B}_{t,k,\ell',\ell'})} \frac{(B_{0,\ell'} B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)} \right\} \tag{39}$$

where

$$R\left((B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}; \hat{p}_k, \hat{\Xi}_\ell, \mu_{\ell'}\right) = \gamma^{\eta-1}(1-\gamma)^{1+\eta\frac{1-\gamma}{\gamma}}(1-\mu_{\ell'}^{-1})\mu_{\ell'}^{-\eta\frac{1-\gamma}{\gamma}} \hat{\Xi}_\ell^{1-\eta} \hat{p}_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} \tag{40}$$

given conjectures $(\hat{p}_k, \hat{\Xi}_\ell)$ for prices and research productivity, and conjecture $(\hat{B}_{t,k,\ell',\ell'})$ for local research on each pest.

Proof. Let $V_{k,\ell',\ell}$ be the total profit of farmers in ℓ who choose (k, ℓ'). We can write

$$\begin{aligned} V_{k,\ell',\ell} &= \pi_{k,\ell',\ell} \mathbb{E}[V_i^* | u_i^* = (k', \ell'')] \\ &= \pi_{k,\ell',\ell} \Xi_\ell \\ &= \gamma^\eta (1-\gamma)^{\eta\frac{1-\gamma}{\gamma}} \Xi_\ell^{1-\eta} p_k^{\frac{\eta}{\gamma}} q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} \end{aligned} \tag{41}$$

where the first line is a definition, the second line uses the result of Lemma 2, and the third line re-writes $\pi_{k,\ell',\ell}$ from Lemma 2 in terms of the productivity index Ξ_ℓ and simplifies. The total expenditure of farmers on the (k, ℓ') technological good is $\frac{1-\gamma}{\gamma} V_{k,\ell',\ell}$, since farmers retain fraction γ of revenues (see Lemma 1) and spend fraction $(1-\gamma)$ on the input. Moreover, fraction $1-\mu_{\ell'}^{-1}$ of this expenditure is the innovator's revenue net of costs, since $\mu_{\ell'}$ is the markup over the marginal cost (normalized to one). We therefore write the revenue $R_{k,\ell',\ell}$ of innovator ℓ' in the (k, ℓ) market as

$$\begin{aligned} R_{k,\ell',\ell} &= (1-\mu_{\ell'}^{-1}) \left(\frac{1-\gamma}{\gamma} V_{k,\ell',\ell} \right) \\ &= (1-\mu_{\ell'}^{-1}) \left(\frac{1-\gamma}{\gamma} \gamma^\eta (1-\gamma)^{\eta\frac{1-\gamma}{\gamma}} \hat{\Xi}_\ell^{1-\eta} \hat{p}_k^{\frac{\eta}{\gamma}} q_{k,\ell',\ell}^{-\eta\frac{1-\gamma}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} \right) \\ &= \gamma^{\eta-1}(1-\gamma)^{1+\eta\frac{1-\gamma}{\gamma}}(1-\mu_{\ell'}^{-1})\mu_{\ell'}^{-\eta\frac{1-\gamma}{\gamma}} \hat{\Xi}_\ell^{1-\eta} \hat{p}_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} \end{aligned} \tag{42}$$

where the second line substitutes in Equation 41 and the third line substitutes in $q_{k,\ell',\ell} = \mu_{\ell'}$, the pricing policy, and re-arranges terms. This third line defines the function R defined in Equation 40 in the Lemma's statement.

The innovator's objective, for each (k, ℓ) pair, is to maximize net revenue minus research costs. Combining Equation 42 with the expression for costs (Equation 4), and accounting for the fact that innovators receive only fraction $e^{-\rho_{\ell',\ell}} \leq 1$ of net revenue due to trade, licensing, and IP costs, yields Equation 39.

□

A.2 Proof of Proposition 1

Fix crop k, innovator country ℓ', and downstream market ℓ. We first derive an expression for the quality of the transferred technology, $\theta_{k,\ell',\ell}$. Program 39, derived in Lemma 3, is concave under the maintained assumption that $\eta(1-\alpha) < 1+\phi$ (Footnote 7). Observe first that, 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

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

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 $K_1(\mu_{\ell'}) = (1-\mu_{\ell'}^{-1})\mu_{\ell'}^{-\eta\frac{1-\gamma}{\gamma}}$ 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

$$\begin{aligned}\log B_{t,k,\ell',\ell} = {} & \frac{\log\left(K_0(\gamma,\eta)\eta(1-\alpha)\right)}{1+\phi} - \log B_{0,\ell'} - \frac{\rho_{\ell',\ell}}{1+\phi} + \frac{1-\eta}{1+\phi}\log\Xi_\ell + \frac{\eta}{\gamma(1+\phi)}\log p_k \\ & + \frac{1}{1+\phi}\log K_1(\mu_{\ell'}) + \frac{\eta}{1+\phi}\log\omega_{k,\ell} + \frac{\eta}{1+\phi}\log\theta_{k,\ell',\ell} + \frac{1}{1+\phi}\tau(B_{t,k,\ell',\ell'})\end{aligned} \tag{43}$$

We next substitute Equation 43 into the definition of $\log\theta_{k,\ell',\ell}$ (Equation 3) to write

$$\begin{aligned}\log\theta_{k,\ell',\ell} = {} & \alpha\log A_{k,\ell'} + (1-\alpha)\frac{\log\left(K_0(\gamma,\eta)\eta(1-\alpha)\right)}{1+\phi} - (1-\alpha)\log B_{0,\ell'} - \frac{(1-\alpha)\rho_{\ell',\ell}}{1+\phi} \\ & + \frac{(1-\alpha)(1-\eta)}{1+\phi}\log\Xi_\ell + \frac{(1-\alpha)\eta}{\gamma(1+\phi)}\log p_k + \frac{(1-\alpha)\eta}{1+\phi}\log\omega_{k,\ell} + \frac{(1-\alpha)}{1+\phi}\log K_1(\mu_{\ell'}) \\ & + \frac{(1-\alpha)\eta}{1+\phi}\log\theta_{k,\ell',\ell} + \frac{1-\alpha}{(1+\phi)T}\sum_{\tau\in\mathcal{T}_{k,\ell}}\tau(B_{t,k,\ell',\ell'})\end{aligned} \tag{44}$$

We now simplify the last term on the right-hand-side. Let $B_{k,\ell'} > 0$ be a conjectured solution to Equation 43 for any $t \in \mathcal{T}_{k,\ell'}$ or "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

$$\frac{1-\alpha}{(1+\phi)T} \sum_{\tau \in \mathcal{T}_{k,\ell}} \tau(B_{t,k,\ell',\ell'}) = \frac{1-\alpha}{1+\phi}(1-\delta_{k,\ell',\ell})\tau(B_{k,\ell'}) + 0 \cdot \delta_{k,\ell',\ell} = \frac{1-\alpha}{1+\phi}(1-\delta_{k,\ell',\ell})\tau(B_{k,\ell'}) \tag{45}$$

We finally derive the desired expression for technology transfer, in quantity units. As show in Lemma 3 (Equation 41), total expenditure on the technological input is

$$E_{k,\ell',\ell} := \frac{1-\gamma}{\gamma} V_{k,\ell',\ell} = \frac{R_{k,\ell',\ell}}{1-\mu_{\ell'}^{-1}} = \gamma^{\eta-1}(1-\gamma)^{1+\eta\frac{1-\gamma}{\gamma}} \mu_{\ell'}^{-\eta\frac{1-\gamma}{\gamma}} \hat{\Xi}_{\ell}^{1-\eta} \hat{p}_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} \theta_{k,\ell',\ell}^{\eta} \tag{46}$$

Since the price is $q_{k,\ell',\ell} = \mu_{\ell'}$, the physical quantity demanded is $X_{k,\ell',\ell} = \mu_{\ell'}^{-1} E_{k,\ell',\ell}$. Finally, taking logs and substituting in Equations 44 and 45, we write

$$\log X_{k,\ell',\ell} = \beta_{k,\ell'} \cdot \delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell,\ell'} \tag{47}$$

where the coefficient is

$$\beta_{k,\ell'} = -\frac{\eta(1-\alpha)\tau(B_{k,\ell'})}{1+\phi-\eta(1-\alpha)} \tag{48}$$

and one representation of the fixed effects is

$$\begin{aligned}
\chi_{k,\ell} &= \left(\frac{(1-\alpha)\eta}{1+\phi-\eta(1-\alpha)} + \eta\right) \log \omega_{k,\ell} + \chi_k + \chi_\ell + \chi \\
\chi_{k,\ell'} &= \frac{\eta\alpha(1+\phi)^{-1}}{1+\phi-\eta(1-\alpha)} \log A_{k,\ell'} + \chi_{\ell'} \\
\chi_{\ell,\ell'} &= -\frac{\eta(1-\alpha)}{1+\phi-\eta(1-\alpha)} \rho_{\ell,\ell'}
\end{aligned} \tag{49}$$

where

$$\begin{aligned}
\chi &= \frac{1-\alpha}{1+\phi-\eta(1-\alpha)} \log(K_0(\gamma,\eta)\eta(1-\alpha)) + \log K_0(\gamma,\eta) \\
\chi_k &= \frac{\eta}{\gamma}\left(\frac{1-\alpha}{1+\phi-\eta(1-\alpha)} + 1\right) \log p_k \\
\chi_\ell &= (1-\eta)\left(\frac{1-\alpha}{1+\phi-\eta(1-\alpha)} + 1\right) \log \Xi_\ell \\
\chi_{\ell'} &= -\frac{(1-\alpha)(1+\phi)^{-1}}{1+\phi-\eta(1-\alpha)} \log B_{0,\ell'}
\end{aligned} \tag{50}$$

The representation of fixed effects is not unique, as each term in the set $(\chi, \chi_k, \chi_\ell, \chi_{\ell'})$ can be

represented in at least two different two-way fixed effects.

Having proved the Proposition, we conclude with a brief discussion of the model's interpretation of the fixed effects representation in Equation 49. The crop-by-destination fixed effect $\chi_{k,\ell}$ controls for the effects of destination suitability, crop prices, and overall destination productivity. The crop-by-origin fixed effect $\chi_{k,\ell}$ controls for the general productivity of origin technology and the research costs in the origin. The origin-destination fixed effect controls for bilateral trade, licensing, and IP frictions.

A.3 Proof of Proposition 2

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

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

or dollar profits divided by γ (the profit share of revenue) and p_k (the price). Thus, using the language of Lemma 2, total production is the sum of expected production given each choice of technology ℓ':

$$Y_{k,\ell} = \sum_{\ell'}^{L} \mathbb{E}\left[\frac{V_i^*}{\gamma p_k} \mid u_i^* = (k, \ell')\right] \cdot \pi_{k,\ell',\ell} \tag{52}$$

As shown in Lemma 2, $\mathbb{E}\left[V_i^* \mid u_i^* = (k, \ell')\right] = \Xi_\ell$ for any (k, ℓ'). By the arguments above,

$$\mathbb{E}\left[\frac{V_i^*}{\gamma p_k} \mid u_i^* = (k, \ell')\right] \equiv \frac{\Xi_\ell}{\gamma p_k} \tag{53}$$

and hence, returning to Equation 52,

$$\begin{aligned} Y_{k,\ell} &= \frac{1}{\gamma p_k} \Xi_\ell \sum_{\ell'}^{L} \pi_{k,\ell',\ell} \\ &= \frac{1}{\gamma p_k} \Xi_\ell \sum_{\ell'}^{L} \left(\theta_{k,\ell',\ell}^{\eta} \omega_{k,\ell}^{\eta} p_k^{\frac{\eta}{\gamma}} \Xi_\ell^{-\eta} \gamma^{\eta} (1-\gamma)^{\eta\frac{1-\gamma}{\gamma}}\right) \\ &= \gamma^{\eta-1}(1-\gamma)^{\eta\frac{1-\gamma}{\gamma}} p_k^{\frac{\eta}{\gamma}-1} \Xi_\ell^{1-\eta} \omega_{k,\ell}^{\eta} \sum_{\ell'}^{L} \theta_{k,\ell',\ell}^{\eta} \\ &= \gamma^{\eta-1}(1-\gamma)^{\eta\frac{1-\gamma}{\gamma}} p_k^{\frac{\eta}{\gamma}-1} \Xi_\ell^{1-\eta} \omega_{k,\ell}^{\eta} \Theta_{k,\ell}^{\eta} \end{aligned} \tag{54}$$

where the second line substitutes the expression for $\pi_{k,\ell',\ell}$ derived in Lemma 2, the third line collects terms, and the fourth defines $\Theta_{k,\ell} = (\sum_{\ell'=1}^{L} \theta_{k,\ell',\ell}^{\eta})^{1/\eta}$.

Taking a log, we derive the desired form

$$\log Y_{k,\ell} = \eta \log \Theta_{k,\ell} + \tilde{\chi}_k + \tilde{\chi}_\ell + \eta \log \omega_{k,\ell} \tag{55}$$

where one representation of the fixed effects is

$$\begin{aligned} \tilde{\chi}_k &= \left(\frac{\eta}{\gamma} - 1\right) \log p_k \\ \tilde{\chi}_\ell &= (1-\eta) \log \Xi_\ell + (\eta - 1) \log \gamma + \eta \frac{1-\gamma}{\gamma} \log(1-\gamma) \end{aligned} \tag{56}$$

As additional results, alluded to in the main text, we derive analogous expressions for planted area and physical yield. First, total planted area of crop k is the sum of planted area of each (k, ℓ) pair: $\pi_{k,\ell} = \sum_{\ell'=1}^{L} \pi_{k,\ell',\ell}$. Applying Lemma 2 and simplifying gives

$$\log \pi_{k,\ell} = \eta \log \Theta_{k,\ell} + \eta \log \omega_{k,\ell} + \frac{\eta}{\gamma} \log p_k - \eta \log \Xi_\ell + \eta \log \gamma + \eta \frac{1-\gamma}{\gamma} \log(1-\gamma) \tag{57}$$

Finally, observe that physical yield $z_{k,\ell}$ equals production per unit area. Thus

$$\log z_{k,\ell} = \log Y_{k,\ell} - \log \pi_{k,\ell} = \log \Xi_\ell - \log p_k - \log \gamma \tag{58}$$

A.4 Optimal Pricing of the Technological Good

In this appendix, we micro-found our assumption that the innovator prices the technological good at (monopolist-specific) markup $\mu_{\ell'}$. We first study the conventional model in which the innovator behaves as a monopolist, in which case the markup is $\mu_{\ell'} = (1-\gamma)^{-1}$ for all ℓ'. We next study a variant model in which the innovator perceives $\sigma_{\ell'} \in [1, \infty)$ times the impact of prices on product demand, where $\sigma_{\ell'}$ can be interpreted as the "conduct parameter" in empirical industrial organization (Bresnahan, 1989). We show that, in this model, we can micro-found markups $\mu_{\ell'} = (1 - \sigma_{\ell'}^{-1}\gamma)^{-1} \in (1, (1-\gamma)^{-1}]$.

Lemma 4. *If the innovator in ℓ' is a monopolist, it charges price $q_{k,\ell',\ell} = (1-\gamma)^{-1}$ for each (k, ℓ) market.*

Proof. Conditional on any choice for quality $\theta_{k,\ell',\ell}$, the monopolist chooses its price to solve

$$\max_{q_{k,\ell',\ell}} \left\{ \int_0^1 (q_{k,\ell',\ell} - 1) \cdot X_{k,\ell',i} \cdot \mathbb{I}[u_i^* = (k, \ell')] \, \mathrm{d}i \right\} \tag{59}$$

where the marginal cost is normalized to one; $X_{k,\ell',i}$ is i's demand for (k,ℓ') inputs, if they were to choose (k,ℓ'); and u_i^* is i's optimal choice of a crop-technology pair. Substituting in the demand curve derived in Lemma 1, and applying the argument of Lemma 2 toward the expectation of idiosyncratic productivity, this can be re-written as

$$\max_{q_{k,\ell',\ell}} \left\{ \left((1-\gamma)^{\frac{1}{\gamma}} p_k^{\frac{1}{\gamma}} (\theta_{k,\ell',\ell}\omega_{k,\ell}) \pi_{k,\ell',\ell} f(\Xi_\ell) \right) (q_{k,\ell',\ell} - 1)\, q_{k,\ell',\ell}^{-\frac{1}{\gamma}} \right\} \tag{60}$$

where $\pi_{k,\ell',\ell}$ is the measure of farmers in ℓ choosing (k,ℓ') and $f(\Xi_\ell)$ is some function of aggregate productivity in ℓ, capturing the conditional expectation of the idiosyncratic component of technology demand. Program 60 is concave. Taking the first order condition yields

$$\left((1-\gamma)^{\frac{1}{\gamma}} p_k^{\frac{1}{\gamma}} (\theta_{k,\ell',\ell}\omega_{k,\ell}) \pi_{k,\ell',\ell} f(\Xi_\ell) \right) \left(q_{k,\ell',\ell}^{-\frac{1}{\gamma}} - \frac{1}{\gamma}(q_{k,\ell',\ell} - 1) q_{k,\ell',\ell}^{-\frac{1}{\gamma}-1} \right) = 0 \tag{61}$$

Re-arranging gives the desired expression

$$q_{k,\ell',\ell} = \frac{1}{1-\gamma} \tag{62}$$

□

Lemma 5. *If the innovator in ℓ' behaves with conduct parameter $\sigma_{\ell'} \in (0,1]$, it charges price $q_{k,\ell',\ell} = (1-\sigma_{\ell'}\gamma)^{-1}$.*

Proof. An innovator with conduct parameter $\sigma_{\ell'}$ internalizes fraction $\sigma_{\ell'}$ of the effect its pricing has on overall demand. The innovator therefore has the modified first-order condition

$$\left((1-\gamma)^{\frac{1}{\gamma}} p_k^{\frac{1}{\gamma}} (\theta_{k,\ell',\ell}\omega_{k,\ell}) \pi_{k,\ell',\ell} f(\Xi_\ell) \right) \left(q_{k,\ell',\ell}^{-\frac{1}{\gamma}} - \frac{\sigma_{\ell'}}{\gamma}(q_{k,\ell',\ell} - 1) q_{k,\ell',\ell}^{-\frac{1}{\gamma}-1} \right) = 0 \tag{63}$$

where $\sigma_{\ell'}$ multiplies the second term in the second parenthesis, which captures the effect on demand of changing the price. Re-arranging yields the desired expression

$$q_{k,\ell',\ell} = \frac{1}{1-\frac{\gamma}{\sigma_{\ell'}}} \tag{64}$$

□

A.5 Mapping to Multiple-Input Model

Here, we show how a variant model with multiple inputs maps to our main model. This clarifies the sense in which our main analysis abstracts away from these other inputs without loss.

Consider, as in our baseline setup, a farm i producing crop k with biotechnology from ℓ'. Departing from the baseline, the farm has a new production function that uses $N+1$ inputs. The first input is the biotechnological input, which was the only input in our main analysis. The production function, supressing dependence on the index i, crop k, and biotechnology source ℓ' for convenience, is

$$Y = X^{1-\gamma-\sum_{n=1}^{N}\alpha_n}\left(\prod_{n=1}^{N} X_n^{\alpha_n}\right)(\theta\tilde{\omega}\varepsilon)^{\gamma} \qquad \forall i \in [\ell-1,\ell) \tag{65}$$

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

$$\max_{X,(X_n)_{n=1}^{N}} \left\{ pX^{1-\gamma-\sum_{n=1}^{N}\alpha_n}\left(\prod_{n=1}^{N} X_n^{\alpha_n}\right)(\theta\tilde{\omega}\varepsilon)^{\gamma} - \tilde{q}X - \sum_{n=1}^{N}\tilde{q}_n X_n \right\} \tag{66}$$

For comparison, in the baseline model with no additional inputs, the farm chooses only the input X to solve

$$\max_{X,(X_n)_{n=1}^{N}} \left\{ pX^{1-\gamma}(\theta\omega\varepsilon)^{\gamma} - qX \right\} \tag{67}$$

where we remove tildes on ω and q to more easily state the equivalence result.

We now state and prove a result that maps between this variant model and our baseline model:

Lemma 6. *The multiple-input model implies the same farm-level profits as the one-input model where*

$$\begin{aligned} q_{\ell'} &= \tilde{q}_{\ell'}^{\frac{1-\gamma-\sum_{n=1}^{N}\alpha_N}{1-\gamma}} \\ \omega_{k,\ell} &= \tilde{\omega}_{k,\ell} K(\alpha,\gamma)^{\frac{1}{\gamma}}\left(\prod_{n=1}^{N} q_n^{-\alpha_n}\right) \end{aligned} \tag{68}$$

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

$$X = \frac{(1-\gamma-\sum_{n=1}^{N}\alpha_n)pY}{q} \qquad\qquad X_n = \frac{\alpha_n pY}{q_n}\,\forall n \tag{69}$$

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

$$Y = \frac{K(\alpha,\gamma)^{\frac{1}{\gamma}}\theta\omega\varepsilon p^{\frac{1-\gamma}{\gamma}}}{q^{\frac{1-\gamma-\sum_{n=1}^{N}\alpha_n}{\gamma}}\prod_{n=1}^{N}q_n^{\alpha_n}} \tag{70}$$

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

$$\Pi = \gamma pY = \gamma\cdot\left(p^{\frac{1}{\gamma}}q^{-\frac{1-\gamma-\sum_{n=1}^{N}\alpha_n}{\gamma}}\left(\prod_{n=1}^{N}q_n^{-\alpha_n}\right)K(\alpha,\gamma)^{\frac{1}{\gamma}}\theta\omega\varepsilon\right) \tag{71}$$

Comparing this expression to Equation 25 in Lemma 2, which derived farmer profits in the main model, we see that the models are isomorphic under the following transformation. We re-introduce subscripts i, k, ℓ', and ℓ and let tildes denote parameters as they were used in the variant model of this appendix. We set, in the baseline model,

$$\begin{aligned} q_{\ell'} &= \tilde{q}_{\ell'}^{\frac{1-\gamma-\sum_{n=1}^{N}\alpha_N}{1-\gamma}} \\ \omega_{k,\ell} &= \tilde{\omega}_{k,\ell}K(\alpha,\gamma)^{\frac{1}{\gamma}}\left(\prod_{n=1}^{N}q_n^{-\alpha_n}\right) \end{aligned} \tag{72}$$

The first equation reflects the fact that the new model predicts a different elasticity of farm profits to the biotechnological input's price. This is immaterial for any of our model's predictions, as this price is fixed at the ℓ' level. The second equation incorporates the (inverse) price of the other inputs into our measure of crop-by-location level productivity. Intuitively, a country in which crop-k specific variable inputs (e.g., machinery) are cheap is, enveloping over the optimal choice of those inputs, more productive per unit of land.

The last claims about equivalent implications for technology development, technology transfer, production, and productivity follow from recognizing that all of this paper's subsequent results characterizing these objects depend on farmers' behavior only through profit function and input demand derived in Lemma 1. □

A.6 Social Versus Private Incentives

In this appendix, we contrast the private incentives for pest and pathogen research with public incentives. To define the social planner's problem, we must first take a stand on the preferences of the representative consumer, from which we derived global demand curves $(p_k)_{k=1}^K = d((Y_k)_{k=1}^K)$. We assume that the economy has, in addition to the K crops, a numeraire good representing the rest of the economy. Consumption of this good, which we denote as M, can be negative. The representative household's preferences are represented by some function $u : \mathbb{R} \times \mathbb{R}_+^K$ which takes, as arguments, consumption of the numeraire and total consumption of all of the crops. The household is rebated all profits of all global innovators, who transform the numeraire into research output.

The social planner's problem can be written as

$$\begin{aligned} \max_{(B_{t,k,\ell',\ell})_{k,\ell',\ell,t\in\mathcal{T}_{k,\ell}},(X_{k,\ell',\ell})_{k,\ell',\ell}} & \left\{ u(M,(Y_k)_{k=1}^K) - \sum_{k=1}^K \sum_{\ell=1}^L \sum_{t\in\mathcal{T}_{k,\ell}} e^{-\tau(B_{t,k,\ell',\ell'})} \frac{(B_{0,\ell'} B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)} \right. \\ & \left. - \sum_{k=1}^K \sum_{\ell=1}^L \sum_{\ell'=1}^L X_{k,\ell',\ell} \right\} \\ \text{s.t. } & F_k((B_{t,k,\ell',\ell})_{k,\ell,t\in\mathcal{T}_{k,\ell}},(Y_k)_{k=1}^K) \leq 0, \ \forall k \end{aligned} \tag{73}$$

The planner chooses research levels and quantities produced of the technological good. The functions F_k are defined to encompass the technological possibilities, or the assignment of each farmer i to crop k.

Let λ_k denote the Lagrange multiplier on each dimension of F. Under the assumption that the program in Equation 73 is concave, the following first-order condition for the choice of $B_{t,k,\ell',\ell}$ is necessary for optimality:

$$\begin{aligned} B_{0,\ell'}^{1+\phi} B_{t,k,\ell',\ell}^{\phi} \exp(-\tau(B_{t,k,\ell',\ell'})) = \lambda_k & \frac{\partial F_k((B_{t,k,\ell',\ell})_{k,\ell,t\in\mathcal{T}_{k,\ell}},(Y_k)_{k=1}^K)}{\partial B_{t,k,\ell',\ell}} \\ & + \mathbb{I}[\ell'=\ell]\tau'(B_{t,k,\ell',\ell}) \sum_{\ell''=1}^L e^{-\tau(B_{t,k,\ell',\ell})} \frac{(B_{0,\ell'} B_{t,k,\ell',\ell''})^{1+\phi}}{T(1+\phi)} \end{aligned} \tag{74}$$

The left-hand-term is the marginal research cost, ignoring the externality. The first right-hand-term is the marginal production benefit of increasing research, in utility units (i.e., transformed by the Lagrange multiplier λ_k). The second term appears only for local CPP research, or when $\ell' = \ell$, and it encodes the benefit via the externality on research for all countries ℓ.

A sharp difference between the social planner's allocation versus the equilibrium allocation is that the planner, perceiving these cost reduction benefits, would have researchers in ℓ' invest in research

for pests not present in ℓ' (i.e., with the first right-hand-side term zero), purely to exploit these external benefits. More generally, the presence of these terms increases marginal incentives toward environment-specific research in the social planner's allocation relative to the market allocation.

A.7 An Alternative Source of Inappropriateness: Copycat Innovators

In this Appendix, we describe a model with limited IP and "copycat innovators" that derives similar conclusions to our baseline setting.

Our setting for production is the same as the baseline described in Section 1.1. Our structure of innovation is different. First, innovation is only possible in one country which, without loss, we index as $\ell = 1$. Moreover, innovators in this country receive profits only from technology sold in the home country. We can encode this by assuming that the iceberg cost is is

$$\rho_{\ell,\ell'} \begin{cases} 0 & \text{if } \ell = \ell' = 1 \\ \infty & \text{otherwise} \end{cases} \tag{75}$$

Our interpretation, as in Acemoglu and Zilibotti (2001), is that imperfect contract enforcement and IP protection prevents innovators in the technology-producing "North" ($\ell = 1$) from obtaining profits in the other countries which comprise the "South." We assume that the market structure and costs faced by innovators in $\ell = 1$ are the same as in our baseline model, although these details are immaterial for some of our main conclusions in this model variation.

Next, we assume that there exist "copycat" innovators in each country $\ell \neq 1$ that can adapt country 1's technology and sell their version at zero cost. Specifically, if country 1 produces crop-k technology with general attribute A_k and pest-specific attribute $B_{t,k}$, the copycat technology has quality

$$\log \theta_{k,1,\ell} = \alpha \log A_k + \frac{1-\alpha}{T} \sum_{t \in \mathcal{T}_{k,\ell}} \max \left\{ \log B_{t,k}, \log \underline{B}_\ell \right\} \tag{76}$$

for some $\log \underline{B}_\ell > -\infty$. In words, the copycat can reproduce the general and specific qualities of the North's technology, and can substitute a local practice with productivity $\underline{B}_\ell$ to deal with any local pest or pathogen threat. As indicated by our notation, the copycat's innovation exactly plays the role of international technology sourced from country 1 in farmer's choices and, by extension, aggregate productivity.

Proposition 2, as stated, holds exactly in this economy as it does not depend directly on the structure of endogenous innovation. To derive an analogy to Proposition 1, we first observe that the innovative North will develop quality $B_{t,k} \equiv B_k$ to combat all ecological threats $t \in \mathcal{T}_{k,1}$ and $B_{t,k} = 0$ for all $t \notin \mathcal{T}_{k,1}$. The argument for this result is exactly the same as the one given in the proof of

Proposition 1. Under the assumption that $\log B_k > \log \underline{B}$, we can re-write Equation 76 as

$$\log \theta_{k,1,\ell} = \alpha \log A_k + (1-\alpha)\left((1-\delta_{k,1,\ell})\log B_k + \delta_{k,1,\ell}\log \underline{B}\right) \tag{77}$$

where $\delta_{k,1,\ell}$ is the fraction of non-shared CPP threats, as in the main analysis. We can therefore write the following equation for the quality or intensity of *copycatting* that mirrors our representation for technology diffusion in Proposition 1:

$$\log \theta_{k,\ell',\ell} = \beta_{k,\ell'} \cdot \delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell,\ell'} \tag{78}$$

In this case, the fixed effects are given by

$$\begin{aligned} \chi_{k,\ell} &= 0 \\ \chi_{k,\ell'} &= \mathbb{I}[\ell' = 1]\left(\alpha \log A_k + (1-\alpha)\log B_k\right) \\ \chi_{\ell',\ell} &= 0 \end{aligned} \tag{79}$$

and the coefficient of interest is

$$\beta_{k,\ell'} = -\mathbb{I}[\ell' = 1](1-\alpha)(B_k - \underline{B}_\ell) \tag{80}$$

In words, the marginal effect of inappropriateness is high when technology is very CPP-specific (low α) and when the gap between frontier and local technology is larger (high $B_k - \underline{B}_\ell$). This parallels the prediction of our baseline model under $\tau' > 0$ (see the discussion in Section 1.2).

B. Additional Empirical Analysis

B.1 Invasive Species

In our baseline estimates, we construct CPP mismatch using all known CPPs present in each country that affect each crop. This measure captures the true extent of global differences in CPP ecology across crops and countries. An important question is whether the baseline findings are driven in part by relatively recent species invasions, or if they are driven predominantly by persistent differences in ecology across crops and locations. As discussed in the main text, there are several prominent examples of how persistent differences in CPP environment shape the effectiveness of technology (see Section 2.1). However, if the results are strongly driven by invasive species, it would be important to explore further the causes of species movement and ensure that they are not correlated with omitted factors that could drive our results.

To investigate the role of invasive species, we use an additional data set produced by CABI:

the Invasive Species Compendium (ISC). The ISC is a list of global invasive species, as determined by extensive literature searches. Since the ISC is also a CABI data set, we can use the unique species identifiers to link ISC species to CPC species in our main CPP data set. 748 CPPs from our main sample, or 15% of the original list, are identified as potentially invasive species in the ISC. To construct versions of CPP mismatch that exclude the possible influence of invasive species, we exclude from our calculations any CPP listed in the ISC (i.e., known to be invasive anywhere in the world). We view this as a conservative choice because we do not rely on information about exactly where a specific CPP is invasive instead of native.[43] We then re-produce all of our main estimates using the CPP mismatch measures purged of variation from invasive species.

The estimates are presented in Table A20. We show results corresponding to our analyses of international technology diffusion (columns 1-3), technology adoption in Africa (column 4), and production (column 5). Compared to our baseline estimates, the effects on technology diffusion are (if anything) slightly larger, and the effects on output very similar in standardized units. These findings indicate that the baseline results are not driven by invasive species.

B.2 Inappropriateness Driven By Agro-Climatic Conditions

This section 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.

B.2.1 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.[44] 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).[45] 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

[43] This information is also not systematically collected by CABI or any other source, to our knowledge.

[44] 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).

[45] 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.

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

$$\Delta\hat{x}_{k,\ell,\ell'} = |\hat{x}_{k,\ell} - \hat{x}_{k,\ell'}| \tag{81}$$

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 $\mathcal{X}$:[46]

$$\text{AgroClimMismatch}_{k,\ell,\ell'} = \frac{1}{|\mathcal{X}|} \cdot \sum_{x \in \mathcal{X}} \Delta\hat{x}_{k,\ell,\ell'} \tag{82}$$

B.2.2 Empirical Estimates

We next investigate whether mismatch in agro-climatic features shapes the transfer of technology and global patterns of production. Column 1 of Table A6 re-produces our baseline estimate of Equation 12, our main technology transfer model, on the sample of country-pairs and crops for which all agro-climatic features could be measured. In column 2, we add all ten agro-climatic mismatch measures $\Delta x_{k,\ell,\ell'}$. Consistent with technology also being specific to particular non-CPP features of the environment, the coefficients on the $\Delta x_{k,\ell,\ell'}$ are almost all negative and four are significant at the 10% level. Mismatch in temperature and precipitation are associated with the largest reductions in technology transfer. There is also a significant effect of mismatch in elevation and soil pH. Despite the inclusion of these additional mismatch metrics, however, the coefficient on CPP mismatch barely changes. In column 3, we include the one-dimensional $\text{AgroClimMismatch}_{k,\ell,\ell'}$ instead of the individual $\Delta x_{k,\ell,\ell'}$. The coefficient on agro-climatic mismatch is negative and significant; however, the coefficient on CPP mismatch again remains very similar.

In Table A12, we present our results for production. The dependent variable is log of agricultural output and the regression specification is (15). Column 1 reproduces our baseline estimate of the relationship between CPP mismatch with the frontier and output on the reduced sample on which we were able to estimate all agro-climatic characteristics. The specification in column 2 includes both CPP mismatch and agro-climatic mismatch. While mismatch with the frontier in non-CPP agro-climatic features significantly lowers output, these effects again operate largely independently from CPP mismatch.

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

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

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.

Finally, we estimate our baseline counterfactuals scenario incorporating both CPP mismatch and acro-climatic mismatch, using the estimates from column 3 of Table A12. Our modeling strategy is identical to the one outlined in Section 5.1 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 A11, which is structured in the same way as Figure 7. Incorporating agro-climatic mismatch as an additional shifter of inappropriateness increases our estimate of the overall effect of inappropriateness on productivity. However, as foreshadowed by the estimates in Table A12, 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.

B.3 The Global Direction of Agricultural Innovation

The inappropriate technology hypothesis is based on the premise that global innovation is biased toward the needs and demands of wealthy frontier countries. There are three reasons we expect this bias to exist, which we discuss via the model in Section 1.1. First, if innovation is more likely to occur in rich countries with more biotechnological infrastructure, it may take advantage of local "technology production opportunities." This mechanism is embodied in the local knowledge spillovers and primitive research-cost heterogeneity in the model. It may, in practice, manifest in accumulated expertise, available test fields for breeding or trials, and readily available germplasm for genetic analysis. Second, since wealthy countries tend to be large markets, global innovation which occurs anywhere in the world may still be directed toward their needs as part of profit-maximizing behavior. Third, wealthy countries may be more likely to have effective intellectual property (IP) protection, which also manifests as an effectively larger market.

We study all three of these hypotheses within our global varieties data from UPOV, focusing on novel plant varieties released anywhere in the world since 2000. Let V_k be the count of all unique denominations produced in the world for crop k over this period; this will be our simple measure of global technological progress for a given crop. To quantify the targeting of this technology, we

estimate the following regression model:

$$\ln(V_k) = \alpha + \delta_1 \cdot \log \text{Area}_k + \delta_2 \cdot \log \text{GDPArea}_k + \delta_3 \cdot \log \text{IPArea}_k + \varepsilon_k \tag{83}$$

in which $\log \text{Area}_k$ is the (log of) global area devoted to crop k, and the other two regressors are respectively this area weighted by per-capita GDP (averaged over 1990-1999) and the presence of intellectual property for plant varieties as of 2000:[47]

$$\log \text{GDPArea}_k = \log\left(\sum_\ell \text{Area}_{k,\ell} \cdot \text{GDP}_\ell\right) \qquad \log \text{IPArea}_k = \log\left(\sum_\ell \text{Area}_{k,\ell} \cdot \mathbb{I}_\ell^{IP}\right) \tag{84}$$

We think of the first regressor, and its coefficient δ_1, as a proxy for each crop's importance to global livelihoods when *not* adjusted by production and/or willingness to pay for technology; while the latter two regressors, and their coefficients (δ_2, δ_3), could each capture bias via the channels described above.

Figure A2 reports our estimates of δ_2 and δ_3, in the form of partial correlation plots. Consistent with the hypothesis, both are positive and significant, and together have an incremental R^2 of 29%. To give a sense of the estimated magnitudes, suppose the global market size of cotton increased by 1%; the estimates imply that, if this expansion occurred in the United States, the number of cotton varieties developed would increase by 4.41%; if it occurred in Brazil, a less wealthy country but one that protects IP, the number of cotton varieties developed would increase by 1.31%; and if it occurred in India, a low-income country that does *not* protect IP, there would be essentially no effect.

To zoom in on the knowledge spillovers channel, we also estimate the following model:

$$\log(V_{k,\ell}) = \delta_0 \log \text{Area}_{k,\ell} + \delta_1 \log \text{Area}_k + \delta_2 \log \text{GDPArea}_k + \delta_3 \log \text{IPArea}_k + \chi_\ell + \varepsilon_{k,\ell} \tag{85}$$

in which $V_{k,\ell}$ is the number of varieties of crop k developed in country ℓ since 2000, and χ_ℓ are country fixed effects. The term $\text{Area}_{k,\ell}$ isolates "local focus," potentially due to local specificity of technology production, relative to all innovators' uniform desire to cater to large markets, as captured by the next three terms. Estimates of (85) are reported in Table A4. We find that $\delta_0 \gg 0$, suggesting that the local focus of innovators is an important mechanism; δ_2 and δ_3 are also positive, although only marginally significant. Un-weighted global market size is uncorrelated with variety development ($\delta_1 = 0$).

Together, this evidence suggests that in our data, technology development is biased toward the demands of wealthy, IP-protecting countries; this effect appears driven by the fact that innovation takes place *in* these countries and innovators develop technology for their home markets. These

[47] We compile country-level information on variety IP protection from UPOV.

estimates mirror our findings using the CPP-specific patent data in Section 2.4 and further motivate the local R&D spillovers in the model.

B.4 Technology Transfer to Africa

The UPOV data set tracks all plant variety certificates and as a result only covers countries for which intellectual property protection is in place. This results in several omissions, most notably much of Africa (Figure A1). To partially fill this gap, we compile data from the Consultative Group on International Agricultural Research (CGIAR) Diffusion and Impact of Improved Varieties in Africa (DIIVA) project. DIIVA has collected data on improved crop varieties for 28 countries in sub-Saharan Africa and across 19 crops since 1960.

Using the DIIVA Project data, we compute the number of varieties for each plant species introduced in 28 African countries; since we do not know the country of origin of each variety, in order to investigate whether inappropriateness is a barrier to technology using these data, we estimate a simplified version of (12):

$$y_{k,\ell} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \tag{86}$$

where $\text{CPPMismatchFrontier}_{k,\ell}$ is defined using either method described in Section 4.1. We expect CPP mismatch with the frontier to inhibit technology transfer; that is, we hypothesize that $\beta < 0$. Estimates of Equation 86 are reported in Figure A3. Consistent with our main technology transfer results estimated at the country pair-by-crop level, we find that CPP mismatch with frontier significantly inhibits biotechnology introduction in sub-Saharan Africa. While these estimates are necessarily less precise, given the smaller sample size and absence of data on the origin country, they tell a very similar story to our main analysis.

B.5 Technology Adoption in Africa

In this appendix, we study how inappropriateness affects production on smallholder farms in sub-Saharan Africa, which have received substantial attention for the low penetration of agricultural technology in spite of ostensible benefits (see, e.g., Suri, 2011; Duflo et al., 2011). Our specific question is the extent to which the inappropriateness of frontier technology explains low use of improved inputs.

To measure the use of improved technologies, we combine data from the latest geo-coded round of all Living Standard Measurement Survey (LSMS) Integrated Surveys of Agriculture (ISA). These are detailed surveys on all facets of agricultural production, including technology use, collected by the World Bank in collaboration with the statistical agencies of eight countries: Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda. Data are collected at the field and

farm level.

Our dependent variable, $\text{ImprovedSeed}_{k,z}$, is a crop-by-farm indicator for the use of improved seeds (i.e., not locally bred varieties), as reported in the LSMS-ISA survey. One shortcoming of this measure is that self-reported data on improved seed use is not always accurate. For example, Kosmowski et al. (2019) compare survey evidence to DNA re-analysis in Ethiopia and find that farmers are accurate approximately 60% of the time. Our assumption is that this measurement error is not systematically correlated with CPP mismatch across cross-country pairs and conditional on our control variables.

Our main estimating equation is:

$$\text{ImprovedSeed}_{k,z} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell(z)} + \chi_{\ell(z)} + \chi_k + \varepsilon_{k,z} \tag{87}$$

where k continues to index crops and z indexes farms in the LSMS-ISA data. The regressor $\text{CPPMismatchFrontier}_{k,\ell}$ is defined using either method described in Section 4.1. The dependent variable is an indicator that equals one if farmer z uses an improved seed variety for crop k. χ_k denotes crop fixed effects and $\chi_{\ell(z)}$ denotes country fixed effects. If the inappropriateness of technology reduces technology adoption, we would expect that $\beta < 0$; however, it is possible that the smallholder farmers in the sample are not likely to use improved technology regardless of its appropriateness, and the context specificity of frontier innovation is not an important barrier to productivity enhancements in this setting.

Our findings are reported in Table A8, where CPP mismatch is measured either as CPP mismatch with the measured set of crop-specific frontier countries (Panel A) or CPP mismatch with the US (Panel A). Across specifications, we find a negative and significant relationship between adoption and CPP mismatch. The estimates of column 1 imply that improved seed use by the median farmer in our sample would be 14% more prevalent absent inappropriateness, relative to an in-sample mean of 17.9%. The estimates are similar after including state fixed effects (column 2) or a quadratic polynomial in farm latitude and longitude (column 3) in order to control more flexibly for the local geography. Our findings are also similar when the regression is weighted by farm size (column 4) or using our two alternative constructions of CPP mismatch (columns 5-6).

These estimates indicate that inappropriateness contributes toward low improved input use on some of the world's least productive small farms. Through the lens of our model, in which endogenous innovation responds to demand for inputs, they further suggest a reason why research and marketing investment from global biotechnology firms has not materialized in sub-Saharan Africa (Access to Seeds Foundation, 2019).

C. CPP Threats and Plant Breeding: Extended Discussion

Crop pests and pathogens (CPPs), which include 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), which represents "possibly the greatest threat to productivity" across all environments (Reynolds and Borlaug, 2006, p. 3). In Brazil, a major agricultural producer, it is estimated that 38% of annual production is lost due only to insects (Gallo et al., 1988), amounting to $2.2 billion in lost output per year (Bento, 1999). Prior to the development of transgenic corn, the Western Corn Rootworm alone caused $1 billion in annual losses in the US and substantially more around the world (Gray et al., 2009). A critical focus of crop breeding, as a result, is developing resistance to damaging CPPs.

The most fundamental technique for breeding favorable plant traits, including those that confer CPP resistance, is mass selection: saving the seeds of the "best" plants from a given crop cycle, re-planting them the next year, and repeating the process (McMullen, 1987, p. 41). This process naturally selects crop lineages with sufficient resistance to the local CPP environment. But it creates no selective pressure for resistance to non-present CPP threats, and such resistance is extremely unlikely to arise by chance mutation.

Historians have written extensively about how the environmental-specificity of traditional breeding severely limited the diffusion of agricultural technology in the 20th century. Moseman (1970, p. 71) argues that US programs during the 1960s to increase agricultural productivity in other countries via technological diffusion largely failed because of the "unsuitability of U.S. temperate zone materials [...] to tropical agricultural conditions." In a review of agricultural technology diffusion, Ruttan and Hayami (1973, p. 122) state that "ecological variations [...] among countries inhibit the direct transfer of agricultural technology." The location specificity of breeding has, anecdotally, been a major barrier to technology diffusion.

There are a handful of examples of the international transfers of crop biotechnology across environments, but these exceptions often prove the rule. Reynolds and Borlaug's (2006) detailed account of one uncommonly successful program of international crop diffusion, the CIMMYT wheat program, makes clear the time and resources required to overcome these obstacles with coordinated international breeding. The authors describe, as one example, how cooperation between CIMMYT laboratories and the Brazilian Institute of Agricultural Research (EMPRAPA) enabled the production of semi-dwarf wheat varieties adapted to Brazil's acidic soil and distinct CPP environment. This process involved more than a decade of intense coordination and the development of a novel "shuttle breeding" program to breed alternate generations of plants in different locations. EMBRAPA itself, a state-owned agricultural research organization whose mission is to develop agricultural technologies that are well suited to the Brazilian context, is an example of the type of investment in local research

that may allow countries to overcome the "inappropriate technology problem." However, there are few examples in the world at that scale.

In recent decades, genetic modification (GM) has been added to the crop development toolkit. The vast majority of modern GM technology has directly related to 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 process of natural selection in the field and consequent obstacles to breeding for non-local environments. But, in practice, GM technology has been used almost exclusively for solving the pathogen threats facing high-income countries, due to these countries' higher demand (Herrera-Estrella and Alvarez-Morales, 2001).

An illustrative case study of how modern plant varieties are "locally" targeted comes from Bt varieties, a large and celebrated class of genetically modified plants. Bt varieties are engineered to express crystalline proteins, cry-toxins, that are naturally produced *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 maize rootworm (Munkvold and Hellmich, 1999), major threats in the US and Western Europe. δ-endotoxins produced by Bt were originally identified as candidate toxins specifically because of their effectiveness against these particular pests (Bessin, 2019). Indeed, Monsanto's Bt corn varieties, MON863 and MON810 were developed with δ-endotoxins selected for their effectiveness against maize rootworm, which, as it turns out, is relatively uncommon among Cry proteins (Galitsky et al., 2001).

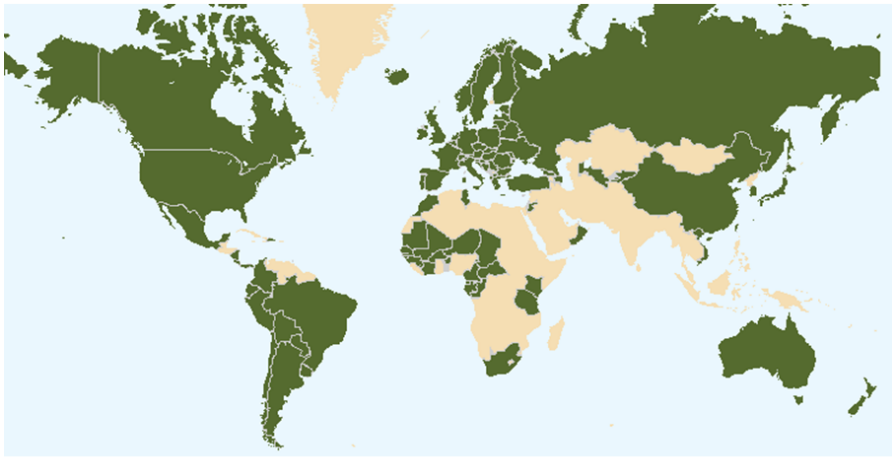
In other parts of the world with different CPP threats, however, frontier Bt maize is neither commonly used nor effective. For example, in South Africa there is widespread resistance to Bt maize and production damage caused by the maize stalk borer, which does not exist in the US but is widespread in sub-Saharan Africa (Campagne et al., 2017). As one additional example of the large disparities in research focus on these pests: in our analysis of biotechnology patents described in the main text, we were able to identify only five patents globally related to the maize stalk borer, while we identified 5,007 related to the European maize borer. Disparities in the international appropriateness of GM technologies therefore emerge as a result of focus on "rich-world pests."

This pattern in GM development and research intensity is not restricted to corn. The first varieties of Bt Cotton introduced in the early 1990s were focused on limiting the damage caused jointly by the tobacco budworm, cotton bollworm, and pink bollworm. In India, outbreaks of the pink bollworm in particular pose a major threat to cotton production (Fand et al., 2019). But frontier biotechnology has not adapted to patterns of Bt-resistance in India (or any other low-income countries) due to the

lower relevance of the pink bollworm threat in the United States (see Tabashnik and Carrière, 2019, for a review of pink bollworm resistance in global cotton populations). In recent years, the desert locust (see Figure 1, bottom panel) has caused substantial damage in East Africa, causing major losses across several crops and concerns about food security (Salih et al., 2020); yet just 14 patents have ever been issued related to the desert locust and biotechnological solutions to this pest threat are limited. The same is true of the spotted stem borer, which causes an estimated $450 million in losses each year in East Africa (corresponding to 15-100% in yield losses depending on the location), but has been the subject of limited research (53 patents) (Pratt et al., 2017).

D. Supplementary Figures and Tables

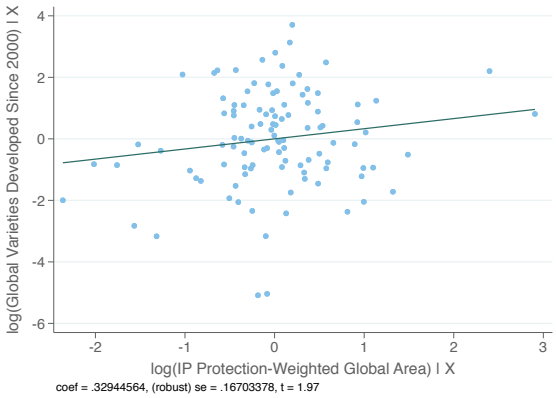
Figure A1: UPOV Compliant Countries



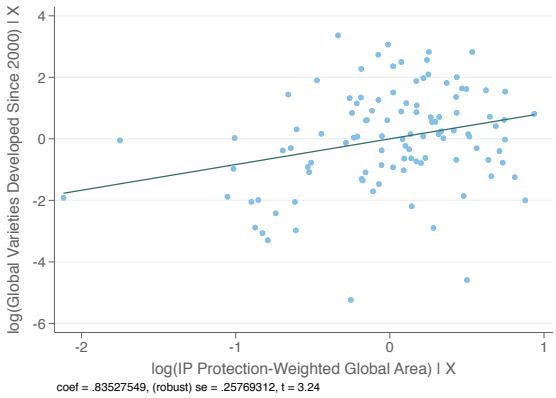
Notes: This figure denotes in green all UPOV member countries. This is the sample of countries for which we have data on biotechnology development and transfer.

Figure A2: Bias in Global BioTech Development

(a) IP-Weighted Area and BioTech Development



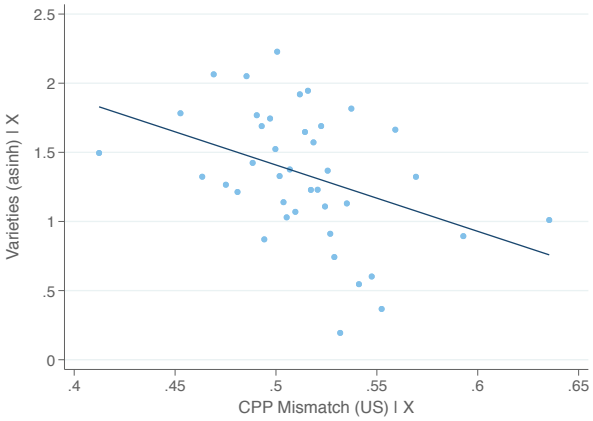
(b) GDP-Weighted Area and BioTech Development



Notes: Partial correlation plots ($N = 107$) of our estimates of δ_2 and δ_3 from Equation (83). Both are estimated from the same regression, which also includes a control for log of global planted area.

Figure A3: CPP Mismatch and Biotechnology Transfer to sub-Saharan Africa

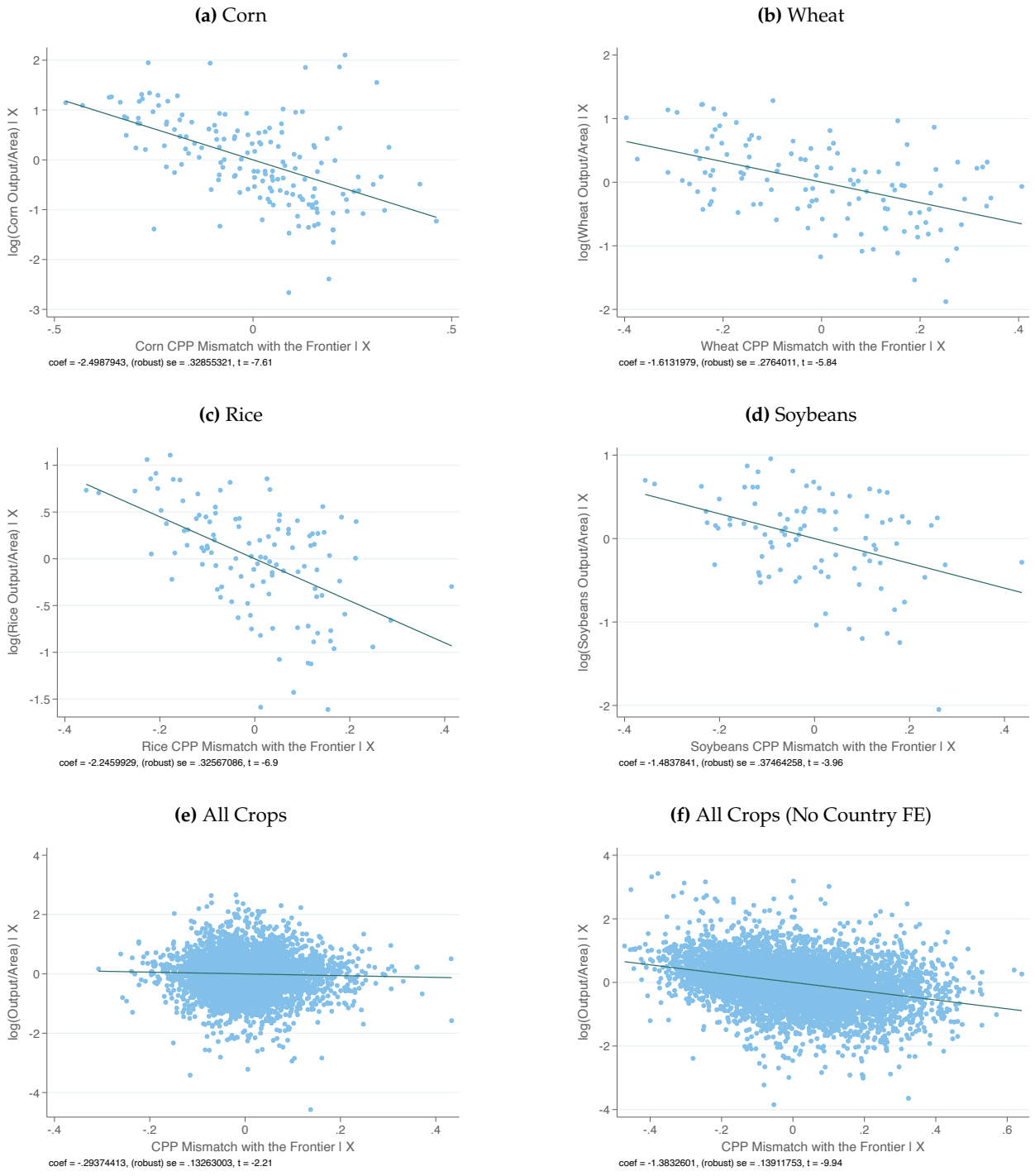
(a) Mismatch with the US



(b) Mismatch with Estimated Frontier Countries

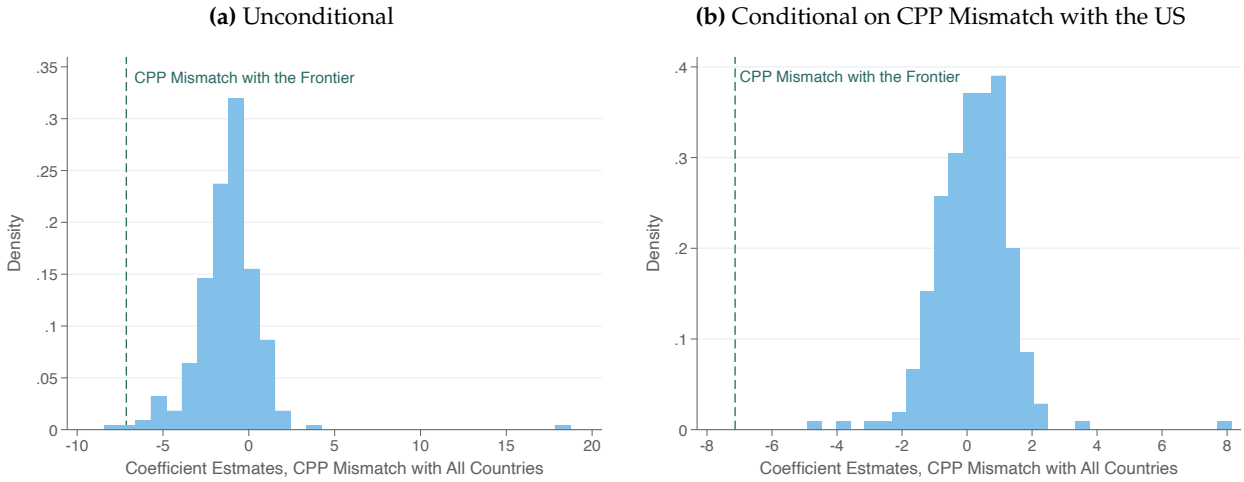
Notes: This figure displays binned partial correlation plots, after absorbing country and crop fixed effects, of our estimates of Equation (86), both using pathogen distance to the US (left) and pathogen distance to the estimated frontier set (right). The number of observations is 345 in both sub-figures and standard errors are clustered by country.

Figure A4: CPP Mismatch and Agricultural Yield



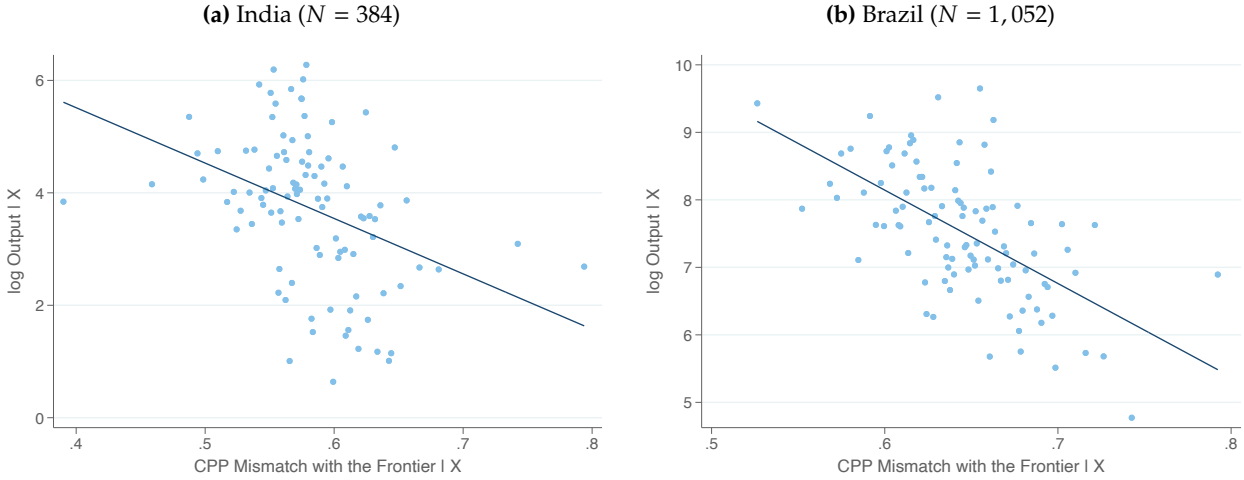
Notes: Each sub-figure reports a partial correlation plot of (15). In A4a - A4d we restrict the sample to corn, wheat, rice, and soybeans respectively. In A4e and A4f the sample includes all crops and in A4f country fixed effects are removed from the regression equation. The dependent variable is log of output per acre. The coefficient estimates and standard errors are noted at the bottom of each sub-figure.

Figure A5: Falsification Test: CPP Mismatch with All Countries and Output (2000s)



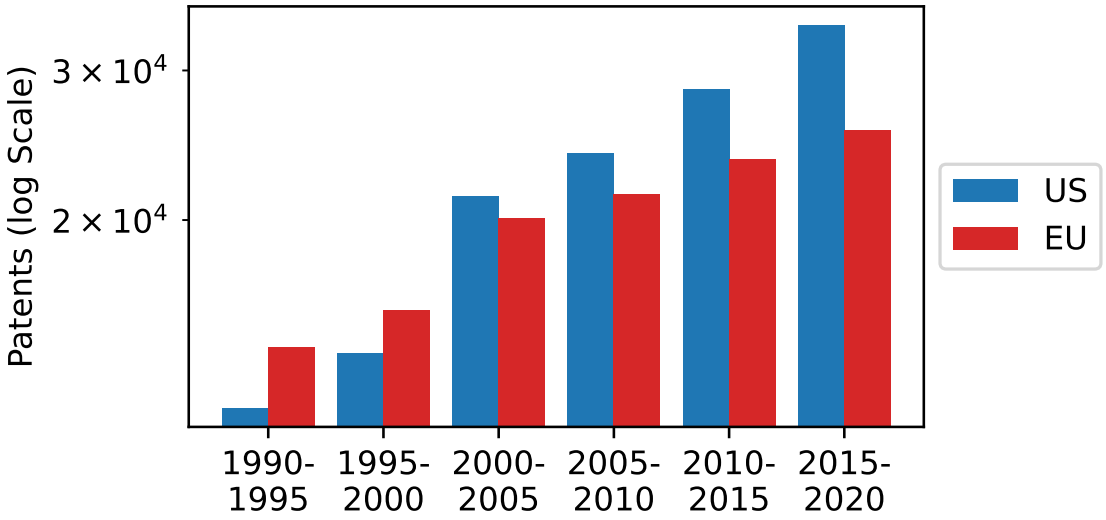
Notes: This figure displays histograms of the coefficient estimates of the relationship between CPP mismatch with each country separately and log of crop-level output. In A5a, CPP mismatch with each country is included on the right hand side of the regression alone (along with crop and country fixed effects) and A5b, CPP mismatch with the frontier is also included in the regression.

Figure A6: CPP Mismatch and Agricultural Output: Brazil and India Separately



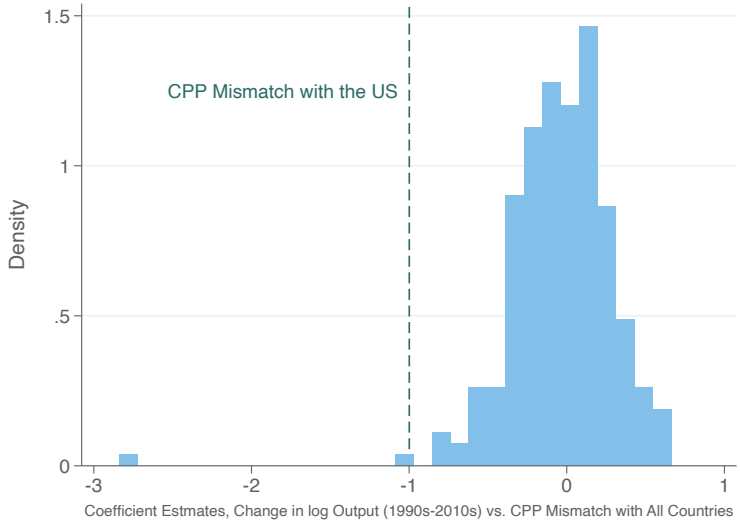
Notes: This figure displays binned partial correlation plots, after absorbing crop and state fixed effects, of our estimates of Equation (16), separately for India (A6a), where we estimate $\beta = -9.85$ (3.59), and Brazil (A6b), where we estimate $\beta = -13.83$ (2.16).

Figure A7: Growth in Patented Agricultural Technologies, Europe vs. the United States



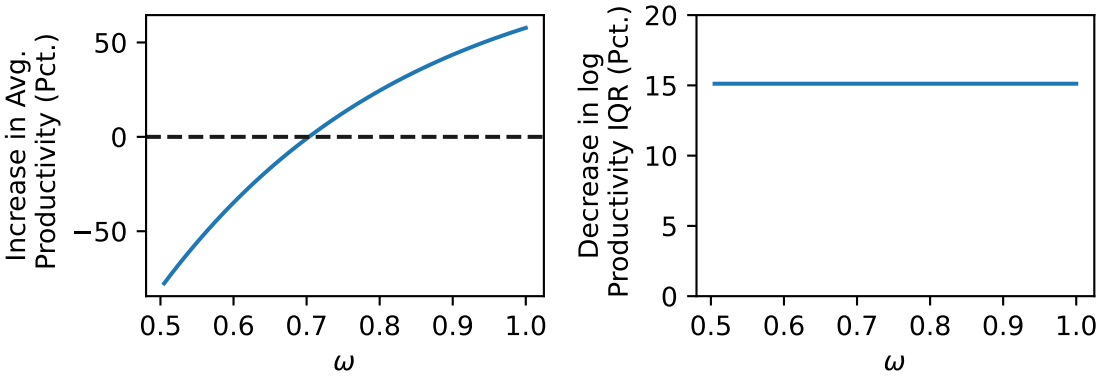
Notes: Total number of patented agricultural technologies (i.e., in CPC class A01) in each five year period, comparing patents with assignees in the US to patents with assignees in the modern EU (as of 2018). Bars are the number of patents issued in the five year bin noted on the horizontal axis.

Figure A8: 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. The effect of CPP mismatch with the US is marked with a dotted line. The implied p-values from this permutation test is $p = 0.004$.

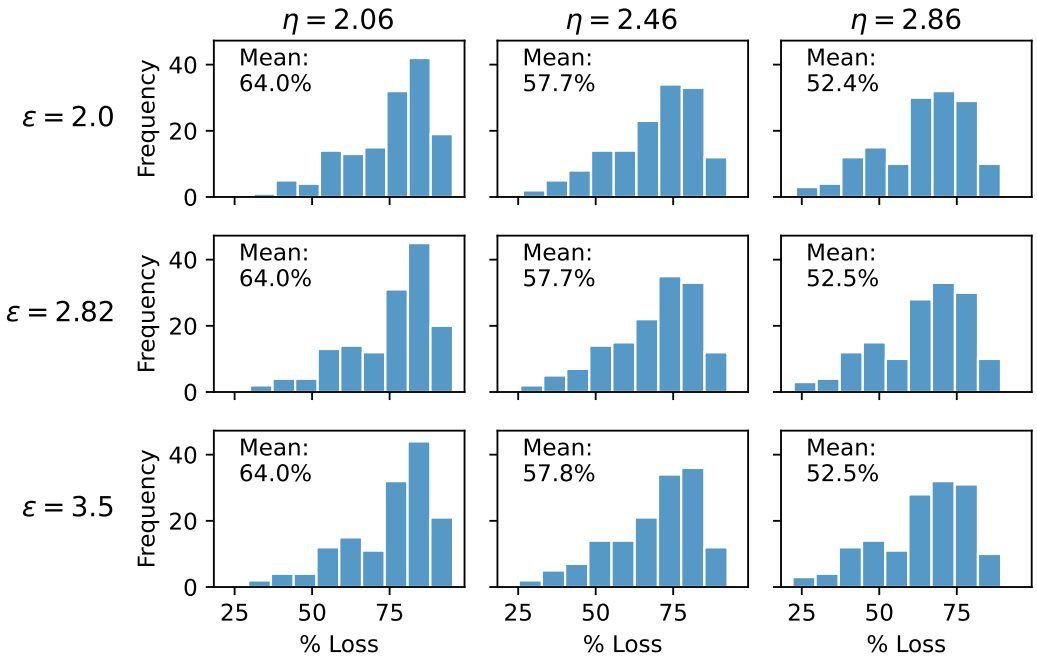
Figure A9: Causal Effects of Inappropriateness, Against Different Baselines



Notes: The graphs plot the increase in average productivity (left) and decrease in productivity disparities (right) due to inappropriateness, relative to different baseline scenarios parameterized by ω.

Figure A10: Sensitivity Analysis of Counterfactual Experiment

(a) Losses by Country



(b) Losses vs. Observed Productivity

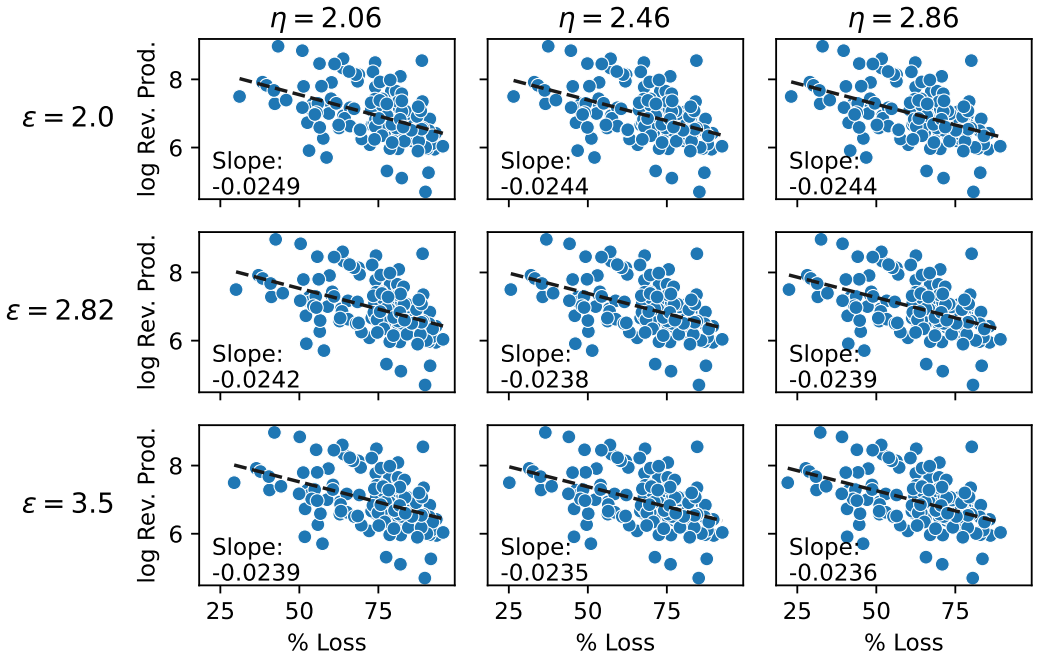
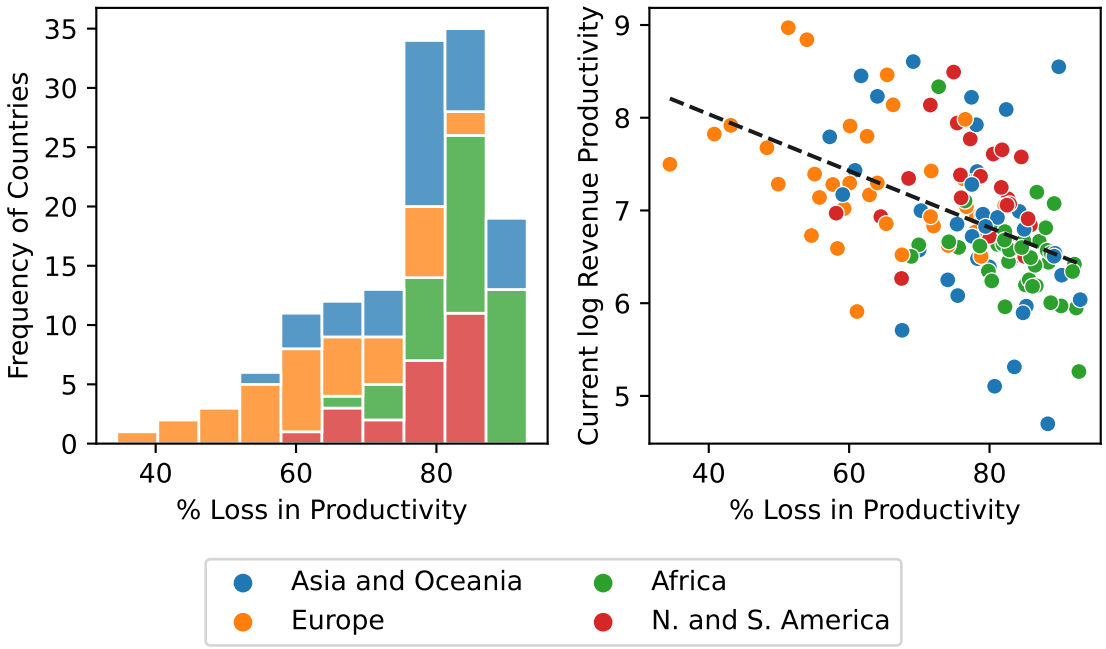
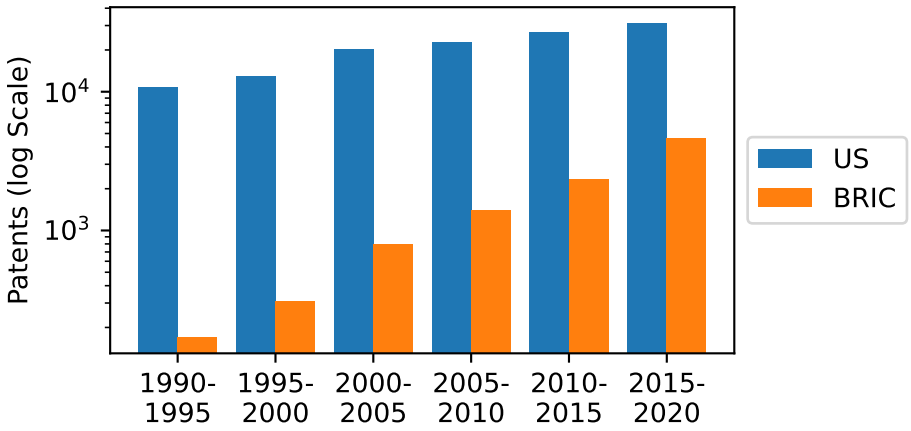


Figure A11: Causal Effects of Inappropriateness: CPP and Agro-Climatic Mismatch



Notes: This figure recreates Figure 7 under an experiment that removes inappropriateness due to both CPP mismatch and Agro-Climatic mismatch. 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.

Figure A12: Growth in Patented Agricultural Technologies, BRIC vs. the United States



Notes: 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 Brazil, Russia, India, or China, from one of the five major patent offices (USPTO, WIPO, EPO, JPO, KIPO). Bars are the number of patents issued in the five year bin noted on the horizontal axis.

Table A1: Correlation Matrix: 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: Patenting Activity Directed Toward Local CPPs

	(1) CPP-Specific Patents (asinh)	(2) Any CPP-Specific Patent (0/1)	(3) log CPP-Specific Patents
Local CPP	0.0972***	0.0479***	0.181***
	(0.0288)	(0.0106)	(0.0635)
Country Fixed Effects	Yes	Yes	Yes
CPP Fixed Effects	Yes	Yes	Yes
Observations	492,422	492,422	8,557
R-squared	0.211	0.202	0.557

Notes: The unit of observation is a CPP-by-country pair. The dependent variable is the number of patents registered to inventors in the country and with the CPP's scientific name in the title, abstract, or patent description. Standard errors, clustered by country and CPP, are included in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A3: Patenting Activity Directed Toward Local CPPs: Larger Effects in Rich Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	CPP-Specific Patents (asinh)	Any CPP-Specific Patent (0/1)	log CPP-Specific Patents	CPP-Specific Patents (asinh)	Any CPP-Specific Patent (0/1)	log CPP-Specific Patents
Local CPP	0.0720***	0.0395***	0.142*	0.147***	0.0679***	0.172***
	(0.0242)	(0.00887)	(0.0711)	(0.0418)	(0.0138)	(0.0521)
Local CPP x United States (0/1)	1.002***	0.334***	0.394***			
	(0.0274)	(0.0108)	(0.0825)			
Local CPP x log per-capita GDP (pre-period)				0.0860***	0.0366***	0.0492
				(0.0294)	(0.0101)	(0.0593)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
CPP Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	492,422	492,422	8,557	364,144	364,144	8,478
R-squared	0.233	0.214	0.559	0.240	0.228	0.557

Notes: The unit of observation is a CPP-by-country pair. The dependent variable is the number of patents registered to inventors in the country and with the CPP's scientific name in the title, abstract, or patent description. GDP is computed at the country level from 1990-2000 and normalized by the global mean. Standard errors, clustered by country and CPP, are included in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4: Global Bias of Technology Development: Crop-by-Country Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	asinh(BioTech Since 2000)					
asinh(Local Area)	0.227***	0.213***	0.209***	0.204***	0.204***	0.155***
	(0.0125)	(0.00986)	(0.0112)	(0.00977)	(0.00982)	(0.00842)
asinh(Global Area)		0.0565***	-0.0451	-0.0155	-0.0551	
		(0.0208)	(0.0540)	(0.0310)	(0.0459)	
asinh(GDP-Weighted Area)			0.0925		0.0512	
			(0.0606)		(0.0620)	
asinh(IP-Weighted Area)				0.0814***	0.0625*	
				(0.0309)	(0.0369)	
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	No	No	No	No	No	Yes
Observations	6,758	6,758	6,758	6,758	6,758	6,758
R-squared	0.495	0.501	0.505	0.506	0.507	0.600

Notes: The unit of observation is a crop-by-country pair. The dependent variable is the number of varieties developed in the country for the crop since 2000. Standard errors, clustered by crop, are included in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A5: CPP Mismatch Inhibits International Technology Transfer: Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Dependent Variable is (asinh) Biotechnology Transfers						
CPP Mismatch (0-1)	-0.0624**	-0.113**	-0.0848***	-0.0528**	-0.0572**	-0.0385**	-0.0443***
	(0.0235)	(0.0467)	(0.0258)	(0.0227)	(0.0220)	(0.0186)	(0.0161)
	Panel B: Dependent Variable is Any Biotechnology Transfer (0/1)						
CPP Mismatch (0-1)	-0.0275**	-0.0570**	-0.0373***	-0.0226**	-0.0289***	-0.0204**	-0.0239***
	(0.0106)	(0.0218)	(0.0119)	(0.00998)	(0.0108)	(0.00855)	(0.00821)
	Panel C: Dependent Variable is log Biotechnology Transfers						
CPP Mismatch (0-1)	-1.202***	-0.937*	-0.935**	-1.198***	-1.247***	-1.888***	-1.955***
	(0.386)	(0.523)	(0.363)	(0.390)	(0.444)	(0.502)	(0.666)
Jaccard (1900, 1901) Distance Metric		✓					
Broad CPP Presence Classification			✓				
Control for bilateral crop-level trade				✓			
Control for log bilateral distance x Crop FE					✓		
Exclude country pairs <1000km apart						✓	
Exclude country pairs <2000km apart							✓
Mean of CPP Distance Metric	0.423	0.327	0.413	0.423	0.423	0.423	0.423
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

Notes: The unit of observation is a crop-origin-destination. The dependent variable is noted in the header of each panel and the distance metric, sample restriction, and control set included in each specification is noted at the bottom of each column. Standard errors are double-clustered by origin and destination and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A6: Agro-climatic Mismatch and Technology Transfer

	(1)	(2)	(3)
	Dependent Variable is (asinh) Biotechnology Transfers		
CPP Mismatch (0-1)	-0.0783**	-0.0737**	-0.0752**
	(0.0314)	(0.0309)	(0.0311)
Mismatch in:			
Temperature		-0.0107*	
		(0.00619)	
Precipitation		-0.0141*	
		(0.00807)	
Elevation		-0.00589*	
		(0.00311)	
Ruggedness		-0.000652	
		(0.00246)	
Soil Clay Content		-0.00596	
		(0.00568)	
Soil Silt Content		0.00342	
		(0.00575)	
Soil Coarse Fragment Content		0.000883	
		(0.00318)	
Soil pH		-0.00825**	
		(0.00355)	
Growing Season Length		-0.00453	
		(0.00519)	
Available Water Capacity		-0.00561	
		(0.00466)	
Overall Agro-Climatic Mismatch			-0.0412***
			(0.0129)
p-value joint significance	-	0.007	-
Crop-by-Origin Fixed Effects	Yes	Yes	Yes
Crop-by-Destination Fixed Effects	Yes	Yes	Yes
Country Pair Fixed Effects	Yes	Yes	Yes
Observations	153,038	153,026	153,038
R-squared	0.464	0.464	0.464

Notes: The unit of observation is a crop-origin-destination. Mismatch in agro-climatic features is 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. The agro-climatic index in column 3 is constructed as a sum of the normalized values of the characteristics listed in column 2. Standard errors are double-clustered by origin and destination and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A7: CPP Mismatch with Frontier Countries and Technology Transfer: All Margins

	(1)	(2)	(3)	(4)
Frontier defined as:	United States	Top Variety Developer	Top 2 Variety Developers	Top 3 Variety Developers
	Panel A: Dependent Variable is (asinh) Biotech Transfers			
CPP Mismatch (0-1)	-0.0571**	-0.0453**	-0.0330	-0.0207
	(0.0216)	(0.0215)	(0.0199)	(0.0196)
CPP Mismatch (0-1) x Frontier (0/1)	-0.392***	-1.237***	-1.076***	-1.076***
	(0.0313)	(0.290)	(0.249)	(0.249)
Observations	204,287	204,287	204,287	204,287
R-squared	0.439	0.442	0.444	0.444
	Panel B: Dependent Variable is Any Biotech Transfer (0/1)			
CPP Mismatch (0-1)	-0.0241**	-0.0229**	-0.0181*	-0.0136
	(0.00956)	(0.00986)	(0.00917)	(0.00884)
CPP Mismatch (0-1) x Frontier (0/1)	-0.254***	-0.332***	-0.343***	-0.322***
	(0.0142)	(0.0699)	(0.0623)	(0.0535)
Observations	204,287	204,287	204,287	204,287
R-squared	0.383	0.384	0.385	0.385
	Panel C: Dependent Variable is log Biotech Transfers			
CPP Mismatch (0-1)	-1.161***	-1.084***	-1.154***	-0.852**
	(0.364)	(0.350)	(0.322)	(0.381)
CPP Mismatch (0-1) x Frontier (0/1)	-0.698	-0.694	-0.173	-0.892**
	(1.248)	(0.423)	(0.503)	(0.437)
Observations	5,791	5,791	5,791	5,791
R-squared	0.797	0.797	0.797	0.797
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. The definition of a leader in each specification is noted at the top of each column and the dependent variable is noted in the panel heading. Standard errors are double-clustered by origin and destination and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A8: CPP Mismach Inhibits Biotechnology Adoption in Africa

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is Improved Seed Use (=1)					
	Panel A: CPP Mismach with the Estimated Frontier Set					
CPP Mismatch (0-1)	-0.321***	-0.242***	-0.237***	-0.157***	-0.227***	-0.237***
	(0.0793)	(0.0805)	(0.0812)	(0.0563)	(0.0793)	(0.0812)
Observations	114,605	114,601	114,601	103,968	114,601	114,601
R-squared	0.213	0.246	0.247	0.235	0.246	0.246
	Panel B: CPP Mismatch with the US					
CPP Mismatch (0-1)	-0.220***	-0.186***	-0.185***	-0.147***	-0.205***	-0.314***
	(0.0635)	(0.0610)	(0.0614)	(0.0511)	(0.0689)	(0.0870)
Observations	115,397	115,393	115,393	104,623	115,393	115,393
R-squared	0.213	0.246	0.247	0.235	0.247	0.247
Quadratic Polynomial in Lat and Lon			✓	✓	✓	✓
log Area-Weighted Estimates				✓		
Broad CPP Presence Classification					✓	
Jaccard (1900, 1901) Mismatch Metric						✓
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	-	-	-	-	-
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a plot. In Panel A, CPP mismatch is estimated using the frontier set selected from the UPOV data, and in Panel B it is estimated as CPP mismatch with the US. The controls included in each specification, as well as the mismatch metric when the baseline measure is not used, are noted at the bottom of each column. Standard errors are clustered by crop-country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A9: CPP Mismatch Effects and Innovation

	(1)	(2)
Dependent Variable:	log(BioTech Developed)	IP Protection (0/1)
β^{ℓ}	-0.584***	-0.134***
	(0.159)	(0.0173)
Observations (Countries)	59	242
R-squared	0.173	0.250

Notes: The unit of observation is a country. log(BioTech Developed) is the (log of the) number of unique varieties developed in the country from 2000-2018. IP Protection (0/1) is an indicator variable that equals one if a country had UPOV compliant IP protection for plant biotechnology by 2000. β^{ℓ} refers to the coefficient estimate of the relationship between CPP mismatch with country ℓ and output. Both regressions are weighted by the inverse of the standard error of the estiamte of β^{ℓ}. Robust standard errors are reported and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A10: CPP Mismach Reduces Agricultural Output: Crop × 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 thet 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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A11: CPP Mismatch and Agricultural Output: Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	Panel B: CPP Mismatch with the Estimated Frontier 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***	-10.10***	-10.83***
	(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. Controls included in each specification are noted at the bottom of the column. Standard errors are double-clustered by crop and country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A12: Agro-climatic Mismatch and Agricultural Output

	(1)	(2)
	Dependent Variable is log Output	
CPP Mismatch (0-1)	-7.511***	-6.682***
	(1.361)	(1.344)
Overall Agro-Climatic Mismatch		-1.222***
		(0.318)
Crop Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Observations	4,881	4,881
R-squared	0.574	0.580

Notes: The unit of observation is a crop-country pair. Mismatch in agro-climatic features is 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. The agro-climatic index is constructed as a sum of the normalized values of the individual characteristics. Standard errors are double-clustered by crop and country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A13: 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***	-12.08***	-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	-	p	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 state and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A14: CPP Mismatch Reduces Exports and Increases Price Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline Measure	*Trade*		*Producer Price Volatility*			
Dependent Variable:	log Output	log Exports	log Imports	Price SD (Norm. by Global Mean)		log Price SD	
			Panel B: CPP Mismatch wih the Estimated Frontier Set				
CPP Mismatch (0-1)	-7.136***	-5.386***	-0.415	0.364***	0.212**	0.628***	0.349**
	(0.959)	(0.877)	(0.871)	(0.101)	(0.0978)	(0.177)	(0.176)
Observations	6,704	5,332	5,687	4,481	4,461	4,481	4,461
R-squared	0.600	0.535	0.649	0.243	0.262	0.662	0.668
			Panel A: CPP Mismatch wih the US				
CPP Mismatch (0-1)	-9.285***	-8.768***	1.269	0.523***	0.317***	1.026***	0.671***
	(1.199)	(1.200)	(1.295)	(0.126)	(0.109)	(0.237)	(0.224)
Observations	6,926	5,495	5,854	4,580	4,559	4,580	4,559
R-squared	0.599	0.531	0.647	0.244	0.263	0.661	0.667
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for log Output	No	No	No	No	Yes	No	Yes

Notes: The unit of observation is a crop-country pair. In Panel A, CPP mismatch is measured as CPP mismatch with the estimated set of technological leader countries and in Panel B CPP mismatch is measured as CPP mismatch with the US. The dependent variable is listed at the top of each column and control set listed at the bottom. Standard errors are double-clustered by crop and country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A15: 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 A16: Inappropriateness and the Green Revolution

	(1)	(2)	(3)	(4)	(5)
	Pct. Modern Variety Adoption			Δ log Output	Δ log Area Harvested
CPP Mismatch with GR Breeding Centers	-26.62***	-96.20***	-27.69***	-2.642**	-2.501***
	(9.155)	(27.17)	(9.492)	(1.052)	(0.881)
Crop Fixed Effects	Yes	Yes	-	-	-
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Crop x Continent Fixed Effects	-	-	Yes	Yes	Yes
Only Rice, Wheat, and Maize	No	Yes	No	No	No
Observations	594	104	591	543	543
R-squared	0.406	0.677	0.471	0.419	0.419

Notes: The unit of observation is a country-crop pair. CPP mismatch for each crop is estimated as the CPP distance to the crop-specific Green Revolution main breeding center. All columns include crop and country fixed effects, as well as the pre-period value of the dependent variable, and columns 3-5 also include crop by continent fixed effects. In columns 1-3, the dependent variable is the change in percent (0-100) land area devoted to modern varieties between 1960 and 1980, and in columns 4 and 5 the dependent variable is the change in log output and log area harvested respectively, between the 1960s and the 1980s. Standard errors are double-clustered by country and crop-continent and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A17: Inappropriateness and the Green Revolution: Timing and Geography

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Δ log Output						
Sample:	Baseline Sample			All Africa	All South America	All Asia	All Europe
Time period:	1960s-1980s	1980s-2000s	1990s-2010s	1960s-1980s	1960s-1980s	1960s-1980s	1960s-1980s
CPP Mismatch with GR Breeding Centers	-2.642**	-0.339	-0.544	-1.307	-5.758**	-1.990	0.668
	(1.052)	(0.832)	(0.783)	(0.808)	(1.903)	(1.372)	(1.516)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop x Continent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	543	540	538	277	83	207	118
R-squared	0.419	0.485	0.451	0.343	0.606	0.456	0.542

Notes: The unit of observation is a country-crop pair. CPP mismatch for each crop is estimated as the CPP distance to the crop-specific Green Revolution main breeding center. All columns include country and crop-by-continent fixed effects, as well as the pre-period value of the dependent variable. The dependent variable is the change in log of crop output. The regression sample as well as time period over which the change in output is calculated is listed at the top of each column. Standard errors are double-clustered by country and crop-continent in columns 1-3 and by country in columns 4-7, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A18: Growth of US Biotechnology and Changes in Global Production

	(1)	(2)	(3)	(4)
	Δ log Output		Δ log Area Harvested	
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

Notes: The unit of observation is a country-crop pair. Both CPP mismatch with the US and CPP mismatch with the EU are included in all specifications. 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. 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. Standard errors are double-clustered by country and crop and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A19: Growth of US Biotechnology and Changes in Global Production: Heterogeneity

	(1)	(2)	(3)	(4)
	Δ log Output		Δ log Area Harvested	
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. CPP mismatch with the US is included in all specifications. 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. 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. The major US field crops are corn, wheat, soybeans, and cotton. Standard errors are double-clustered by country and crop and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A20: CPP Mismatch Without Invasive Species: Baseline Estimates

	(1)	(2)	(3)	(4)	(5)
	Technology Transfer			Technology Adoption	Output
Dependent Variable:	asinh Biotech Transfer	Any Biotech Transfer	log Biotech Transfer	Improved Seed (=1)	log Output
CPP Mismatch Without Invasive Species	-0.0712***	-0.0304***	-0.5451		
	(0.0241)	(0.0096)	(0.34)		
CPP Mismatch with the Frontier Without Invasive Species				-0.248***	-6.335***
				-0.0743	(0.948)
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	-	-
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	-	-
Country Pair Fixed Effects	Yes	Yes	Yes	-	-
Country Fixed Effects	-	-	-	Yes	Yes
Crop Fixed Effects	-	-	-	Yes	Yes
Observations	202,154	202,154	5,752	115397	6,858
R-squared	0.4397	0.3831	0.7965	0.213	0.584

Notes: The unit of observation is a crop-origin-destination in columns 1-3, a farm-crop pair in column 4, and a crop-country pair in column 5. Standard errors are double-clustered by origin and destination in columns 1-3, clustered by crop-country in column 4, and double clustered by crop and country in column 5. In all cases, the independent variable is constructed after excluding invasive CPPs. The fixed effects included in each specification are noted at the bottom of each column. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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