Inappropriate Technology: Evidence from Global Agriculture*

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April 19, 2022

Abstract

An influential explanation for the persistence of global productivity differences is that frontier technologies are adapted to the high-income, research-intensive countries that develop them and are significantly less productive if used elsewhere. This paper studies how the environmental specificity of agricultural technology affects its global diffusion and productivity consequences. We use mismatch in the presence of unique crop pests and pathogens (CPPs) as a predetermined shifter of technologies' potential inappropriateness across locations and crops. Inappropriateness predicted by CPP mismatch reduces the cross-country transfer of novel plant varieties, and the inappropriateness of frontier technology reduces crop production. Combining our estimates with an equilibrium model of global research and agricultural specialization, we find that ecological mismatch reduces global agricultural productivity by 42% and increases cross-country disparities by 15%. We use our inappropriate-technology framework to study the uneven productivity consequences of the Green Revolution, the limited use of improved seed varieties in sub-Saharan Africa, and the potential productivity effects of the emergence of new R&D leaders and of ecological disruption due to climate change.

*We thank Daron Acemoglu, Marios Angeletos, David Atkin, Abhijit Banerjee, Ricardo Caballero, Arnaud Costinot, Dave Donaldson, Michela Giorcelli, Michael Goodin, Gabriel Kreindler, Matt Lowe, Martí Mestieri, Paul Novosad, Nathan Nunn, Ben Olken, Jesse Perla, James A. Robinson, Frank Schilbach, and Chris Udry for advice and comments. We are very grateful to Christine Sherratt and Hope Jansen for their help acquiring the CABI Crop Pest Compendium and to Tomochika Motomura for his support with the UPOV data. We also thank seminar participants at MIT, Harvard, the University of British Columbia, the University of Southern California, the NEUDC, the RIDGE Virtual Forum, and the NBER Development Economics/BREAD Fall 2021 Meeting for helpful feedback. Miriam Zuo provided excellent research assistance.

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1. Introduction

Research and development (R&D), which drives technological progress, is concentrated in a small set of high-income countries. The United States alone accounts for 25% of global R&D investment, and the European Union for a further 20%. By contrast, Africa and and South Asia combined account for merely 3.6%, despite encompassing 42% of the world's population (Boroush, 2020). To what extent do these vast disparities in research intensity underlie global disparities in productivity?

One school of thought starts from the premise that the most transformative technological knowledge is broadly applicable and easily transmittable. It concludes that, in the long run, technology diffusion from the innovative frontier erodes global disparities.[1] A second, contrasting school of thought emphasizes that new technologies are often attached with specific conditions and characteristics of production (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 usefulness in, and diffusion to, other contexts (Stewart, 1978; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001). Therefore, technological progress in the frontier causes productivity to persistently differ across places and to cluster in those "similar" to research leaders. The quantitative relevance and global incidence of these predictions, however, remain mostly unknown.

This paper empirically studies the inappropriate technology hypothesis in a context where all of its premises loom especially large: global agriculture and plant biotechnology. Agriculture features immense and persistent cross-country productivity differences (Caselli, 2005), and global R&D is dominated by a small set of biotechnology firms in rich countries.[2] Despite historical recognition that this inequity may underlie productivity differences, the contemporary research gap is not filled by public-sector research, just 3% of which takes place in low-income regions (Beintema et al., 2012), or philanthropically supported research, which also concentrates in wealthy countries (Vidal, 2014).

The core of our strategy for testing and quantifying the inappropriate technology hypothesis is a new measure of potential biotechnological inappropriateness based on the

[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 a majority of countries in sub-Saharan Africa lack a single private sector research program (Access to Seeds Foundation, 2019).

global distribution and crop-specificity of crop pests and pathogens (CPPs). CPPs are extensively documented as pre-eminent threats to agricultural productivity and targets for biotechnological innovation (Savary et al., 2019). Our analysis exploits the fact that a given crop-country's CPP environment is a predetermined shifter of the potential effectiveness of a foreign technology originally developed for a different CPP environment. We then investigate each pillar of the inappropriate technology hypothesis by studying the relationship between this determinant of appropriateness and global innovation, technology diffusion, and production. We use these estimates, interpreted via a model, to quantify the impact of the (in)appropriateness of technology on the global distribution of agricultural productivity and to study the effects of counterfactual changes to global research and ecology.

Toward these goals, we first describe a model of production and endogenous innovation in global agriculture. Farmers around the world choose which crops to grow and what international technologies to use. Profit-maximizing innovators in each country invest in improving both context-neutral attributes of technology and context-specific adaptation to location- and crop-level environmental features. Local economies of scale, in the form of knowledge spillovers, guide innovators toward developing technology adapted to the local environment and hence endogenously "inappropriate" for dissimilar environments. In the aggregate, the global production possibilities frontier 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, and show how to map estimates of these equations to aggregate causal effects.

Next, we describe our strategy to measure the potential inappropriateness of context-specific technology across locations and crops, which is based on the differential prevalence of CPPs.[3] The combination of technology's CPP-specificity with large differences in CPP environments around the world can, anecdotally, constrain the benefits of frontier technologies to a small range of environments. As one example, the Maize Stalk Borer (*Busseola fusca*) that decimates maize in Kenya is not present in the US, while the Western Corn Rootworm (*Diabrotica virgifera virgifera*), nicknamed the "Billion-Dollar Bug" for its impact on US

[3]The CPP environment is not the *only* determinant of the direction of innovation and appropriateness of technology. In Appendix B.2 we explore the role of non-CPP differences in agro-climatic conditions.

production, is not present in Kenya (Nordhaus, 2017). While the Western Corn Rootworm has been a major target for the development of resistant, genetically modified varieties, the Maize Stalk Borer has received no such attention and, as a result, genetically modified maize varieties are often ineffective in sub-Saharan Africa (Campagne et al., 2017).

To systematically study examples like the previous, we compile data on the global distribution and host-plant species of all known CPPs—including viruses, bacteria, parasitic plants (weeds), insects, and fungi—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 modern ecological sciences (e.g., Bebber et al., 2013, 2014; Savary et al., 2019).

We first verify that global research is on average focused on CPP threats present in rich countries. Using the CABI location data in combination with comprehensive data on global agricultural patents that mention specific CPPs, we document that research is highly skewed toward CPPs that are present in rich, research-intensive countries. This finding is explained by the interaction of disproportionate focus on locally present CPPs with the uneven global distribution of patenting, consistent with our model.

We then develop a *CPP Mismatch* measure that 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. Thus, we can conduct all subsequent analysis holding fixed differences, ecological or otherwise, purely across crops or purely across country-pairs.

Our first main question is how inappropriateness shapes global technology diffusion. We construct a unique data set on all international instances of intellectual property (IP) protection for agricultural biotechnology 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 find that CPP mismatch substantially lowers cross-border transfer of technology conditional on all two-way fixed effects to absorb any average differences across country pairs or crop-specific conditions at the origin or destination. In our most conservative model, CPP dissimilarities reduce international technology transfer by 30% for the median crop and country-pair. These effects increase drastically, between six- and thirty-fold, when sub-setting to origins with more active biotechnology sectors, revealing the especially large cost of being environmentally dissimilar from top innovators.

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" by either (i) imposing the United States as the single hub for global agricultural innovation, a fact borne out in our own technology data and consistent with others' analysis (e.g. Fuglie, 2016), or (ii) selecting the countries that develop the highest number of varieties for each crop in the UPOV certificate data. We show that countries produce less of specific crops if their local crop environment is more different from the frontier's, holding fixed country and crop effects and using a range of strategies to control directly for innate local suitability.[4] We find similar effects across regions within countries, using state-level production and CPP distribution data from India and Brazil. The estimated effects are large relative to observed variation in output—a one-standard deviation increase in CPP dissimilarity to the frontier reduces production of a crop by 0.51 standard deviations.

To further illuminate the mechanism for these findings, we next investigate the relationship of inappropriateness with measured technology adoption. We focus on two specific case studies in which disparities in technology adoption are the subject of intense debate. We first study how inappropriateness shaped the consequences of the Green Revolution of the 1960s and 1970s, a concerted effort to shift agricultural innovative focus toward certain tropical regions. We find that the adoption of Green Revolution technology and subsequent expansions of production were severely inhibited in places with high CPP mismatch with the crop-specific locations of breeding program development. These findings underscore how "advantageous ecology" is an outcome of the geography of innovation and, as a result, can change over time as the geography of research evolves. Second, using data from the latest geo-coded round of each World Bank Integrated Survey of Agriculture, we show that improved seed use among African farmers is substantially less likely in location-crop pairs

[4]These strategies are: (i) directly controlling for estimates of crop-specific potential yield in the absence of modern technology from the FAO GAEZ agronomic model, and (ii) a LASSO approach that controls flexibly for a large set of ecological features, separately for each crop, in addition to the direct effect of each CPP.

with greater CPP mismatch with the frontier. Thus, frontier technologies' poor adaptation to African environments may explain a significant portion of their low usage.

We finally return to our model to study the aggregate productivity consequences of our findings. Our calibration combines our estimates of the effect of CPP mismatch on production with external estimates of the supply and demand elasticities, which allow us to account for production reallocation and equilibrium price responses. To benchmark the importance of the studied inappropriate technology mechanism for the observed productivity distribution, we calculate productivity in a counterfactual scenario of "removing inappropriateness" by eliminating the knowledge gap between frontier and non-frontier CPP research. Comparing this scenario with what we observe, we estimate that inappropriateness reduces average global agricultural productivity by 42.2% and explains 15.1% of the distribution's inter-quartile range. The latter finding is driven by the fact that the countries that are most lacking in appropriate biotechnology, especially in Africa and Asia, are also those that are least productive today.

We conclude by studying three more real-world counterfactual experiments. We first use the model to identify the countries in which research investment could have the largest possible 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. We next measure the aggregate and distributional effects of one emerging trend in global research, a shift in investment toward Brazil, Russia, India, and China, and one emerging trend in global ecology, a poleward shift in the habitable range of CPPs due to climate change (Bebber et al., 2013). Our findings, taken together, highlight how productivity differences are an endogenous outcome of global innovative focus and can evolve as the geography, incentive structure, and political economy of global innovation shift over time.

This paper builds on a historic body of work on the how the "appropriateness" of technology shapes productivity differences and technology diffusion (Atkinson and Stiglitz, 1969; Stewart, 1978; Griliches, 1957). Recent work in this area has investigated the aggregate consequences of inappropriateness due to differences in capital intensity or skill endowment across countries (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Wilson, 2004; Caselli and Coleman II, 2006; Jerzmanowski, 2007). 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 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). Our analysis suggests that the effect of geography is not fixed, but instead determined as an evolving outcome of endogenous technology development and diffusion.[5] This confluence of ecology and technology diffusion is also 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.

We also build on prior work investigating the sources of international disparities in agricultural production (Caselli, 2005; Lagakos and Waugh, 2013; Gollin et al., 2014; Adamopoulos and Restuccia, 2014). Especially related are analyses of the role of technology in shaping productivity gaps, many of which are focused on the 20th century's Green Revolution (Foster and Rosenzweig, 1996, 2004; Evenson and Gollin, 2003a,b).

At the center our hypothesis 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 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.

Finally, our analysis parallels studies of heterogeneous human disease burdens around the world and their effects on 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.

2. Model

We first embed the "Inappropriate Technology Hypothesis" in a model of agricultural innovation, technology diffusion, and production. Relative to existing models of endoge-

[5] This focus on indirect effects of geography is shared by a parallel literature which emphasizes the intermediating role of political history (e.g., Acemoglu et al., 2001; Nunn and Puga, 2012).

nous inappropriate technology (e.g., Acemoglu and Zilibotti, 2001), we emphasize two features which are central to the context of global agriculture: the possibility for substitution across sectors and production technologies (e.g., crops and crop varieties) and the multi-dimensional nature of environmental differences. We use the model to introduce the key economic mechanisms of the inappropriate technology hypothesis and generate estimable equations with model interpretations. We also return to the model in Section 7 in order to study counterfactual scenarios.

2.1 Set-up

2.1.1 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 its country of origin ℓ'. Given a production technology, the farm purchases $X_{k,\ell',i}$ of a technological input (e.g., seed varieties). The input has price $q_{k,\ell',\ell}$ and destination-specific quality $\theta_{k,\ell',\ell}$, both of which we will endogenize below. The physical output of farm i producing crop k with $X_{k,\ell',i}$ units of quality-$\theta_{k,\ell',\ell}$ technology is

$$\psi_{k,\ell',i} = (X_{k,\ell',i})^{1-\gamma} \left(\theta_{k,\ell',\ell}\omega_{k,\ell}\varepsilon_{k,\ell',i}\right)^{\gamma} \qquad \forall i \in [\ell - 1, \ell) \tag{2.1}$$

where $\gamma \in (0, 1)$ measures the return to fixed factors versus technology; $\omega_{k,\ell}$ is average natural suitability for crop k in country ℓ; and $\varepsilon_{k,\ell',i}$ is an idiosyncratic perturbation with a Fréchet distribution with mean one and shape parameter $\eta > 0$. The random component, specific to and independent across crops k and production technologies ℓ', disciplines the elasticity of average farmer choices to changes in innate or technological productivity, as in Eaton and Kortum (2002) and Costinot et al. (2016).

Farmers choose what crop to grow, from what country to source technology, and how much of the input to buy, given (internationally determined) crop prices p_k and input prices $q_{k,\ell',\ell}$. In Lemma 1, stated and proved in the Online Appendix, we solve for the farmers' optimal input choice and show that the farmers' crop-and-technology choice problem is

$$\max_{k,\ell'} \left\{ \gamma p_k^{\frac{1}{\gamma}} \theta_{k,\ell',\ell}\omega_{k,\ell}\varepsilon_{k,\ell',i} \right\} \tag{2.2}$$

2.1.2 Ecological Characteristics and Ecologically-Specific Technology

There is a set of ecological characteristics indexed by the natural numbers $\mathbb{N}$. Each location-by-crop pair is associated with a set $\mathcal{T}_{k,\ell} \subset \mathbb{N}$ of local ecological characteristics, normalized to size $T > 0$. Direct productivity effects of these characteristics can be modeled in $\omega_{k,\ell}$. Consistent with our empirical analysis, we can think of $\mathcal{T}_{k,\ell}$ describing all locally present crop pests and pathogens (CPPs); we will henceforth use this terminology.

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

$$\theta_{k,\ell',\ell} = \exp\left(\alpha \log A_{k,\ell'} + \frac{1-\alpha}{T} \sum_{t\in\mathcal{T}_{k,\ell}} \log B_{t,k,\ell',\ell}\right) \tag{2.3}$$

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 $B_{t,k,\ell'}$, 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]

2.1.3 Endogenous Innovation

A representative innovator in country ℓ' can develop a technology for each country ℓ and crop k. Innovators choose the price $q_{k,\ell',\ell}$ and the CPP-specific benefits or resistance traits $B_{t,k,\ell',\ell}$ for each (k,ℓ) and $t \in \mathcal{T}_{k,\ell}$ in order to maximize profits. To intensify the focus on incentives for technology's "appropriateness," we assume that $A_{k,\ell'}$ is inelastically fixed.[7]

Innovators' revenues are fraction $\exp(-\rho_{\ell,\ell'}) \leq 1$ of total country-ℓ spending on the technological good, reflecting both trade costs and licensing or IP costs. Their marginal cost to produce inputs is $(1-\gamma)^2$ in terms of a numeraire good.[8] They also face convex, additively

[6] One illustration of this "two-component" structure to agricultural research comes Reynolds and Borlaug (2006)'s account of wheat development at the International Maize and Wheat Improvement Center (CIMMYT) in the 1960s. The authors write that the key challenge was to both improve yields by incorporating a specific semi-dwarfism trait ("A") and to increase resilience to damaging fungal wheat rusts ("B"), whose threat only *increased* as plants become more productive.

[7] Neither of our results (Propositions 1 and 2) relies on this assumption.

[8] This is a convenient normalization, so marginal costs do not show up in expressions for technology

separable research costs. These costs have a power form, parameterized by $\phi > 0$, and have an uninternalized *knowledge spillover* coming from *local* research on the same pest:[9]

$$C_{k,\ell',t}(B) = \exp(-\tau(B_{t,k,\ell',\ell'})) \cdot \frac{(B_{0,\ell'}B)^{1+\phi}}{T(1+\phi)} \tag{2.4}$$

where $B_{0,\ell'} > 0$ is a country-specific constant and the function $\tau : \mathbb{R}_+ \to \mathbb{R}_+$, which is non-decreasing and satisfies $\tau(0) = 0$, controls the knowledge spillover in units of "percentage cost reduction." The knowledge spillover creates a local economy of scale, which could embody the local sharing of ideas and scientific knowledge. More specifically, for agricultural research, it may embody the role of physical inputs with a public-good property like local test fields and local germplasm (genetic material). We will discuss examples of this phenomenon at length in Section 3.1.

Innovators maximize revenues net of costs, given conjectures $(\hat{p}_k, \hat{\Xi}_\ell)$ for crop prices and endogenous revenue productivity in each country ℓ and conjecture $(\hat{B}_{t,k,\ell',\ell'})$ for local research on each pest. In Lemma 3, stated and proved in the Online Appendix, we solve for the optimal price and re-state the country-ℓ' innovator's problem for each (k, ℓ) as

$$\max_{(B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}} \left\{ \frac{(1-\gamma)}{\exp(\rho_{\ell',\ell})} \hat{\Xi}_\ell^{1-\eta} \hat{p}_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} - \sum_{t\in\mathcal{T}_{k,\ell}} \exp\Big(-\tau(\hat{B}_{t,k,\ell',\ell'})\Big) \frac{(B_{0,\ell'}B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)} \right\} \tag{2.5}$$

What Creates Research Disparities? Using Equation 2.5, we can identify the forces in our model that generate inequalities in global technological development. First, innovators in ℓ' have a higher marginal product for CPP-specific innovation in destination ℓ, for any crop k, if the iceberg costs $\rho_{\ell',\ell}$ are low. Chief among the reasons why $\rho_{\ell',\ell}$ may be systematically higher for lower-income ℓ is a lack of effective IP protection (see, e.g., Diwan and Rodrik, 1991; Acemoglu and Zilibotti, 2001). Second, innovators in high-income ℓ' may have systematically lower costs of research, or lower $B_{0,\ell'}$. Impediments to research productivity in low-income countries may include the paucity (or high price) of complementary inputs like physical capital, human capital, or government institutions (Cirera and Maloney, 2017), or the prevalence of financial frictions (Gorodnichenko and Schnitzer, 2013). Third, innovators

transfer and production. If marginal costs were origin and crop specific, they would show up as (log) additive fixed effects at that level in each case.

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

in any country ℓ' may focus more on crop-location pairs (k, ℓ) that have a large endowment of productive land, or high $\omega_{k,\ell}$. Variations of this "market size effect" are documented for other sectors by Acemoglu and Linn (2004) and Finkelstein (2004) and for global agricultural biotechnology in our own analysis of Appendix B.3. 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.

2.1.4 Equilibrium

To close the model, we assume that the vector of prices $(p_k)_{k=1}^K$ lies on a global demand curve $(p_k)_{k=1}^K = d((Y_k)_{k=1}^K)$, where Y_k is total global production of each crop. We define equilibrium as follows:

Definition 1. *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*

1. *Farmers optimize (Equation 2.2), given correct conjectures of prices, and aggregate production and input demand is consistent with a law of large numbers over realized idiosyncratic shocks.*
2. *Innovators optimize (Equation 2.5), given correct conjectures of prices, productivities, and local research.*
3. *Markets clear for each crop, or* $(p_k)_{k=1}^K = d((Y_k)_{k=1}^K)$ *where* $Y_k = \sum_{\ell=1}^L Y_{k,\ell}$.

2.2 Main Predictions

In Appendix A, we include detailed derivations of the model's equilibrium conditions. Here, we highlight the main predictions which motivate our empirical analysis.

2.2.1 Prediction 1: Technology Diffusion

Let $\delta_{k,\ell',\ell}$ be the fraction of k-CPPs that are not shared between locations ℓ and ℓ', or $\delta_{k,\ell',\ell} = \frac{1}{T}|\mathcal{T}_{k,\ell} \cap \mathcal{T}_{k,\ell'}|$. Our first result describes how the quantity of technology transferred, 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*

$$\log X_{k,\ell',\ell} = \beta_{k,\ell'} \cdot \delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell,\ell'} \tag{2.6}$$

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

$$\beta_{k,\ell'} = -\frac{\eta(1-\alpha)\tau(B_{k,\ell'})}{1+\phi-(1-\alpha)\eta} \leq 0 \tag{2.7}$$

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

The proof in Appendix A.2 contains exactly expressions for each of the "fixed effects" as functions of economic primitives.[10] In brief, $\chi_{k,\ell}$ ("crop-by-destination") depends on the destination's market size and productivity; $\chi_{k,\ell'}$ ("crop-by-origin") depends on the scale of research in the innovating country; and $\chi_{\ell,\ell'}$ ("origin-by-destination") is a negative rescaling of the iceberg cost $\rho_{\ell',\ell}$.

Environmental 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 $\tau > 0$), by contrast, innovators in country ℓ' have a "knowledge gap" about local ecological characteristics relative to others and therefore produce more technology for ecologically similar destinations. A lower elasticity of supply (ϕ) and higher elasticity of demand (η) amplify this effect.

If local knowledge spillovers scale with local research, or $\tau(B)$ is strictly increasing, then $|\beta_{k,\ell'}|$ increases in the sending country's CPP research intensity $B_{k,\ell'}$. Under this case of the model, environmental mismatch with the most active innovating countries is most costly for technology transfer. If instead knowledge spillovers were purely on the extensive margin, or $\tau(B) \equiv \tau$ for all $B > 0$, we would observe an equal marginal effect of environmental differences on technology transfer from "high-tech" and "low-tech" sending countries.

In our empirical analysis, we will estimate Equation 2.6 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.

[10]The proof also derives a "regression form" like Equation 2.6 for quality $\log \theta_{k,\ell',\ell}$.

2.2.2 Prediction 2: Specialization and Productivity

We next study the impact of inappropriate technology on production. 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) moves out the production possibilities frontier in any location, it also encourages more production of that crop on relatively less-suitable land. Due to this selection effect, in a model with unobserved plot-level heterogeneity, the appropriateness of technology has ambiguous effects on measured average productivity. We will exploit our parametric assumption of Fréchet-distributed plot-level shocks to derive exact and economically interpretable predictions for observed production, planted areas, and yields, which will allow us to infer the productivity consequences of inappropriate technology.

We first define the *crop technology index* $\Theta_{k,\ell}$ and *revenue productivity index* Ξ_ℓ as a function of local technology and productivity shifters:

$$\Theta_{k,\ell} = \left(\sum_{\ell'=1}^{L} \theta_{k,\ell',\ell}^{\eta} \right)^{\frac{1}{\eta}} \qquad \Xi_\ell = \left(\sum_{k=1}^{K} \Theta_{k,\ell}^{\eta} \omega_{k,\ell}^{\eta} p_k^{\eta} \right)^{\frac{1}{\eta}} \tag{2.8}$$

The following result summarizes the model predictions:

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

$$\log Y_{k,\ell} = \eta \log \Theta_{k,\ell} + \eta \log \omega_{k,\ell} + (\eta - 1) \log p_k + (1 - \eta) \log \Xi_\ell \tag{2.9}$$

Production is monotone increasing in the index of technology from each source country, and hence positive shifters of this index. In Equation 2.9, crop and country fixed effects respectively absorb (international) prices and average local revenue productivity. In the proof of this result in Appendix A.3, we derive also the model's predictions for physical yield and planted area. Because of the Fréchet model's structure for the previously discussed selection effects, log physical yields are predicted to have no relationship with measured technological inappropriateness conditional on country fixed effects.

In Section 5, we will estimate Equation 2.9 using CPP mismatch with an empirically identified technological frontier to span $\log \Theta_{k,\ell}$, crop and country fixed effects to span prices and aggregate revenue productivity, 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 7, we will use the estimates from this analysis plus the model structure to estimate causal effects on revenue productivity.

2.3 Additional Results and Extensions

Before proceding to the empirical anlysis, we briefly summarize additional results and extensions which we present in Supplemental Materials D.

Social vs. Private Incentives. Our main results were stated and proved as conditions for competitive equilibrium. In Supplemental Materials D.1 we present and discuss the social planner's eqiuvalent 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 Supplementary Materials D.2, we derive analogues 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 analogue 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.

3. 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.

3.1 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, replanting 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 maize 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 damaged caused by the 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 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 Supplementary Section E.

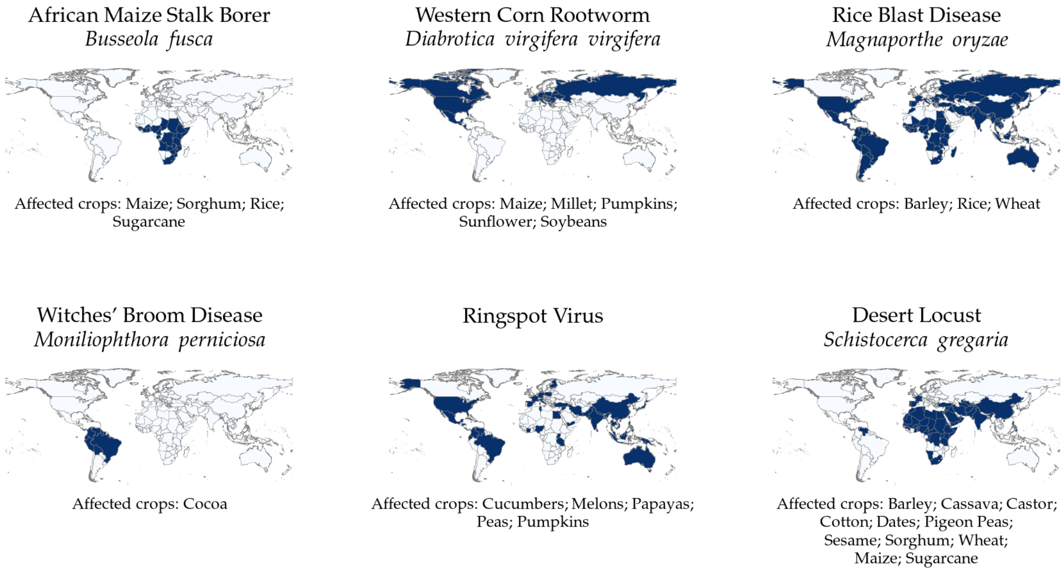
3.2 Plant Pest and Pathogen Data: The Crop Protection Compendium

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 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 joint 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).[11] In total, we compile information on 4,951 plant pests and pathogens, including viruses, bacteria,

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

Figure 1: Data on Example CPPs



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

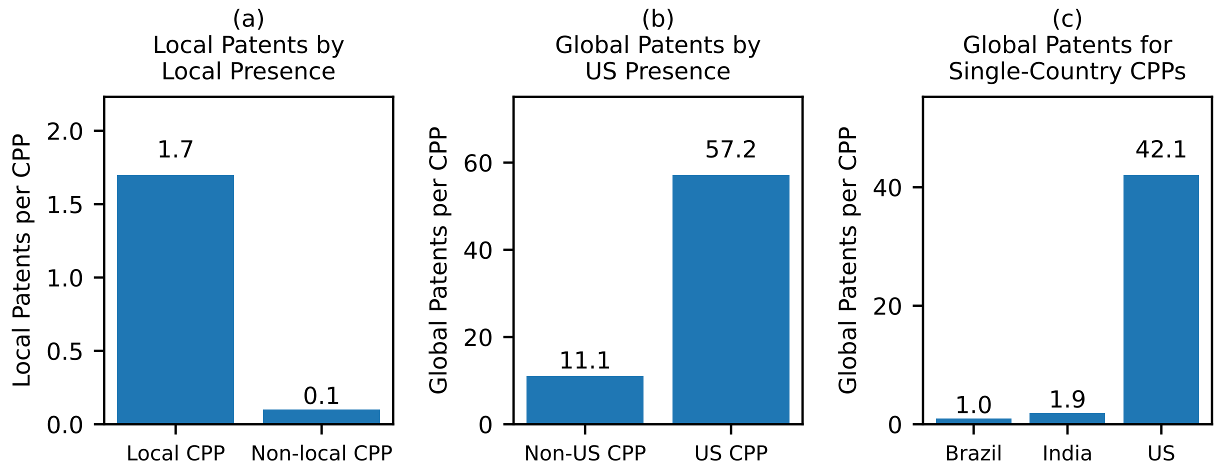
insects, fungi, and weeds.

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 state-level data on the presence of each CPP.[12]

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

[12]A natural question is what forces underly 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. Importantly, 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.

Figure 2: 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.

on 132 host species that are major crops, cross-referenced against the crops used in our subsequent analyses of biotechnology intellectual property and production.

3.3 CPPs and the Direction of Global Innovation

With the CABI CPC data, it is possible to investigate empirically several features of global agricultural innovation discussed in Section 3.1 and built into our model. 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.[13] 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

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

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 2). We investigate this pattern more precisely by estimating the following regression:

$$y_{\ell,t} = \xi \cdot \text{Local CPP}_{\ell,t} + \chi_\ell + \chi_t + \varepsilon_{\ell,t} \tag{3.1}$$

where the unit of observation is a CPP-year and Local $\text{CPP}_{\ell,t}$ 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 fixed effects. ξ captures the extent to which innovation is disproportionately targeted toward local CPP threats. Table A1 reports our estimates. We estimate that $\xi > 0$ in Equation 3.1, 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 2 demonstrates that CPPs present in the US are mentioned by over five times as many patents as those not present in the US. Table A2 reports estimates from an augmented version of (3.1) 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 2 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 end 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.

3.4 Measuring Inappropriateness: CPP Mismatch

The remainder of our empirical analysis starts from the premise of unequal research intensity and studies how ecological differences affect technology diffusion and production. In the model, the scalar summary of ecological difference was the measure of non-common ecological features or 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:

$$\text{CPP Mismatch}_{k,\ell,\ell'} = 1 - \frac{\text{Number of Common CPPs}_{k,\ell,\ell'}}{\left(\text{Number of CPPs}_{k,\ell} \times \text{Number of CPPs}_{k,\ell'}\right)^{1/2}} \tag{3.2}$$

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 (3.2) is one of several standard divergence (one-minus-similarity) measures that satisfy basic properties of *density invariance*, *replication invariance*, and *monotonicity*. Heuristically, 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 by 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 identities of each country's locally present CPPs, a single pair of countries will have different CPP distances across crops. To give one example of this variation, Figure A1 shows the histogram of all countries' CPP mismatch with the US for wheat and sugarcane and identifies the observations for Brazil

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

$$\text{CPP Mismatch}^{J}_{k,\ell,\ell'} = 1 - \frac{\text{Number of Common CPPs}_{k,\ell,\ell'}}{\text{Number of Unique CPPs}_{k,\ell\cup\ell'}} \tag{3.3}$$

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.

and India. For wheat, India is slightly more similar to the US than Brazil is. For sugarcane, Brazil is substantially more similar to the US than India is. These two sources of variation allow us to fully absorb any differences across countries or crops in our empirical analysis.

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. 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 calculation of CPP Mismatch (see Appendix Section B.1).

Non-CPP Mismatch. We also investigate the importance of non-CPP differences in geography, including temperature, precipitation, and soil characteristics, as 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 a shifter 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 4 and 5. 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, and quantitatively smaller than, the effects of CPP mismatch for both outcomes. These results, along with the anecdotal evidence from Section 3.1, motivate our focus on CPP differences in the primary analysis.

4. Main Results: 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 international transfer of plant varieties.

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

4.1 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.[16] 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 A2.[17]

In order 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.[18] 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.[19] 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.

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

[17]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 at various points in the analysis, including with an alternate measure of variety presence in sub-Saharan Africa in Appendix Section B.4).

[18]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.

[19]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 3: Example Rows from UPOV PLUTO 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

Figure 3 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. 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.[20] 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 3.3. 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.

[20]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.

4.2 Empirical Model

Our main estimating equation is the empirical analog of Equation 2.6 in Proposition 1:

$$y_{k,\ell',\ell} = \beta \cdot \text{CPP Mismatch}_{k,\ell',\ell} + \chi_{\ell,\ell'} + \chi_{k,\ell} + \chi_{k,\ell'} + \varepsilon_{k,\ell,\ell'} \tag{4.1}$$

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 effects. These absorb, for example, the fact that certain countries persistently demand or develop more technology for particular crops, as well as any crop-invariant features of country pairs (e.g., physical and cultural distance, geography, trade).[21] Standard errors are double-clustered by origin and destination.

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.

While estimates of β from Equation 4.1 capture the average relationship between CPP mismatch and technology transfer across all countries and crops, Proposition 1 conveyed that the effect of ecological mismatch could be larger when the sending country is very active in research for crop k. To empirically investigate this idea, we estimate versions of the following augmented version of (4.1) that parameterizes heterogeneity in the effect of CPP mismatch:

$$y_{k,\ell',\ell} = \beta_1 \cdot \text{CPPMismatch}_{k,\ell',\ell} + \beta_2 \cdot F_{k,\ell'} \cdot \text{CPPMismatch}_{k,\ell',\ell} + \chi_{\ell,\ell'} + \chi_{k,\ell} + \chi_{k,\ell'} + \varepsilon_{k,\ell,\ell'} \tag{4.2}$$

where $F_{k,\ell'}$ is an indicator variable that equals one for the countries ℓ' that we identify as the biotechnological 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

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

Table 1: CPP Mismatch Inhibits International Technology Transfer

	(1)	(2)	(3)
Dependent Variable:	Biotech Transfer (asinh)	Any Biotech Transfer (0/1)	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.

is motivated by the United States' pre-eminence in modern agricultural research.[22] 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_2 captures the difference in the marginal effect of inappropriateness on technology diffusion when the origin country is a leader in biotechnology development.

4.3 Results

Estimates of Equation 4.1 are reported in Table 1. On all margins, CPP mismatch significantly inhibits the international flow of technology. The estimate from column 3 implies that CPP mismatch inhibits 30% of international technology transfer for the median in-sample level of CPP mismatch.

Before turning to estimates of the effect of CPP mismatch with the *frontier*, we probe the sensitivity of the baseline estimates. Column 1 of Table A3 reproduces our baseline estimates for reference. In column 2 , we show our results are stable using the Jaccard (1900)

[22]The US alone produces 30% of citation-weighted global agricultural science publications. The US is also the global leader in patented agricultural technology and produces 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).

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.

mismatch metric (see Equation 3.3). 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.

We also explore whether the results are influenced by links across countries that are not related to differences in the CPP environment. All specifications include origin-by-destination fixed effects, so any relevant omitted variable must also vary *across crops* within a country pair. Features like geographic or cultural distance between countries are fully absorbed by the country pair fixed effects. In column 4 of Table A3, we control for an indicator that equals one if countries ℓ and ℓ' engage in bilateral final good trade for crop k. 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. Last, Appendix B.2 reports results after controlling for several non-CPP measures of ecological dissimilarity across crops and country-pairs. In all cases, our estimates are quantitatively very similar.

Finally, we estimate the effect of ecological mismatch *relative to the frontier* on technology diffusion. Table 2 reports estimates of (4.2), which includes an interaction term between CPP mismatch and an indicator that equals one if the origin country is a frontier technology developer. 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 A4. 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 of $\beta_2 < 0$ across all specifications in Table 2. 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.

5. Main Results: Production

We now study how mismatch with frontier innovators affects global production.

5.1 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 Agropecuario 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 4.2.

The first 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). Our second 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:

$$\text{CPPMismatchFrontier}^{\text{Est}}_{k,\ell} = \sum_{\ell' \in T(k)} \left(\text{Share Varieties}^{\text{UPOV}}_{k\ell'}\right) \times \left(\text{CPP Mismatch}_{k,\ell,\ell'}\right) \tag{5.1}$$

This method picks up geographic variation in technological leadership, but relies on cross-national comparisons of variety release intensity.[23] For our baseline results, we use $N = 2$; however, the results are very similar for alternative values for N.

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 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 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).

[23] 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.

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.

5.2 Empirical Model

Our main estimating equation is the empirical analog of Equation 2.9 in Proposition 2:

$$y_{k,\ell} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell} + \chi_\ell + \chi_k + \Omega'_{k\ell}\Gamma + \varepsilon_{k,\ell} \tag{5.2}$$

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 and χ_k), which capture any aggregate differences across countries (e.g., income, productivity) or crops (e.g., market size, price). The vector $\Omega_{k,\ell}$ includes proxies for innate suitability, which we vary across specifications. The coefficient of interest is β, which captures the effect of CPP dissimilarity from technology producing countries on features of agricultural production.

5.3 Results

Our baseline estimates of Equation 5.2 are reported in Table 3. In columns 1-4, CPP mismatch with the frontier is measured as mismatch with the US, and in columns 5-8, it is measured as mismatch with the frontier country set, $T_2(k)$. 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 0.5 standard deviations. Figure A3 displays the

Table 3: CPP Mismatch Reduces Agricultural Output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Mismatch with the US				CPP Mismatch with the Estimated Frontier			
CPP Mismatch (0-1)	-9.285***	-10.60***	-9.325***	-8.454***	-7.136***	-5.721***	-7.202***	-6.288***
	(1.199)	(3.024)	(0.617)	(0.652)	(0.959)	(0.663)	(0.461)	(0.501)
log(FAO-GAEZ-Predicted Output)		0.298***				0.353***		
		(0.0814)				(0.0499)		
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	6,926	2,353	6,931	6,069	6,704	2,353	6,707	5,903
R-squared	0.599	0.617			0.600	0.609		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP mismatch with the US and columns 5-8 use CPP mismatch with the estimated set of technological leader countries. 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.

relationship between CPP mismatch with the frontier and crop-specific output visually, for a set of economically important crops: corn, wheat, rice, and soybeans.

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 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, 2021).

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. To make this point explicitly, Appendix Section B.5 documents that the unprecedented rise of US biotechnology research since the 1990s is associated with shifts in global specialization toward crops and countries where US technology is more appropriate. These results, along with related estimates investigating the changing locations of breeding during the Green Revolution which we turn to in Section 6.1, further indicate that our findings are not driven by a static omitted variable, and that "good geographies" can change with the focus of innovation.

Additional Outcomes. Table A5 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 A6 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.[24] The negative relationship with producer price volatility is similar even after holding total output fixed (columns 5 and 7).

Falsification Tests. 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. We re-estimate Equation 5.2, replacing $\text{CPPMismatchFrontier}^{\text{US}}_{k,\ell}$ with CPP mismatch

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

with each country in the world; this generates a series of coefficient estimates $\hat{\beta}^{\ell}$, one for each country. Figure A4 reports histograms of estimates of the $\hat{\beta}^{\ell}$, both from specifications that do not include CPP mismatch with the US as a control (A4a) as well as from specifications that do (A4b). In both cases, the coefficient on CPP mismatch with the US, marked with a dotted line, is the negative coefficient with the highest magnitude. Estimates of the effect of CPP distance to other countries are all smaller in magnitude and centered around zero.

Moreover, the $\hat{\beta}^{\ell}$ are significantly negatively correlated with country-level biotechnology development measured in the UPOV database. Table A7 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 Checks. Table A8 documents that the results are very similar including crop-by-continent fixed effects, which allow us to focus on even more geographically precise variation. Table A9 shows that results are similar after controlling for a broad spectrum of country-level characteristics, including income and agricultural specialization, all interacted with crop fixed effects. The results are also similar after excluding invasive species from the CPP mismatch measure (Appendix B.1) and accounting 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 B2).

5.4 Within-Country Estimates: Brazil and India

Last, we 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:

$$y_{k,s} = \beta \cdot \text{CPPMismatchFrontier}_{k,s} + \chi_s + \chi_{k,\ell(s)} + \Omega'_{k,s}\Gamma + \varepsilon_{k,s} \tag{5.3}$$

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 5.3 are displayed in Table A10, which follows the exact same structure as the baseline country-by-crop estimates in Table 3. We find negative and significant estimates that are very similar in magnitude to our country-by-crop results. For example, in column 1 of Table 3 the coefficient estimate is -9.3 while in Table A10 it is -8.9. The coefficient estimates, if anything, increase when we account for local suitability, either controlling for state-by-crop level FAO GAEZ predicted output (columns 2 and 6), or using our more flexible post double LASSO approach (columns 3-4, 7-8). The findings are also very similar if we focus on either India or Brazil separately (Figure B2). 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.

6. Case Studies: Inappropriateness and Technology Adoption

This section investigates the relationship between inappropriateness and technology adoption in two case studies that are subjects of intense academic and public debate: the uneven consequences of the Green Revolution and the low adoption of modern biotechnology in large parts of sub-Saharan Africa. In doing so, we shed light on a key model mechanism, that inappropriate technology is less likely to be adopted by farmers, and document the extent to which our framework explains important puzzles in the past and present of technology adoption.

6.1 High-Yield Varieties in 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. These centers ultimately coalesced to form the Consultative Group for International Agricultural Research, an organization charged with coordinating international crop development for poor and vulnerable regions (Evenson and Gollin, 2003b).

Usage of Green Revolution varieties and measured productivity growth, however, differed markedly across low-income countries (Evenson, 2005). One potentially important source of this heterogeneity is that varieties developed at the IARCs were inappropriate in places that are ecologically dissimilar from the countries in which the IARCs were located (Binswanger and Pingali, 1988; Lansing, 2009; Pingali, 2012). To empirically investigate whether the inappropriateness of Green Revolution technology shaped its impacts, we first identify from Evenson and Gollin (2003b) the IARC and hence country in which breeding investment for each crop was located (Table A11). We then 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. For example, the IRRI was the main IARC for rice, so in all countries CPPMismatchGR for rice is computed as CPPMismatch with the Philippines.

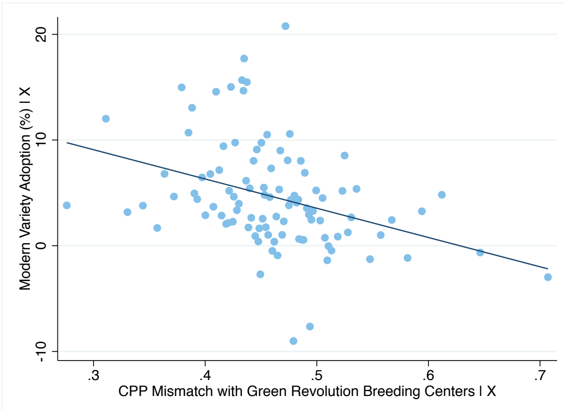
We first study the relationship between $\text{CPPMismatchGR}_{k,\ell}$ and HYV adoption, using data on HYV adoption at the crop-by-country level from Evenson and Gollin (2003a,b). We regress the percent of area devoted to HYVs in 1980-85, a representative cross-section after the bulk of Green Revolution research was conducted, on $\text{CPPMismatchGR}_{k,\ell}$:

$$\text{HYVAdoption}_{k,\ell,1985} = \beta \cdot \text{CPPMismatchGR}_{k,\ell} + \chi_\ell + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \tag{6.1}$$

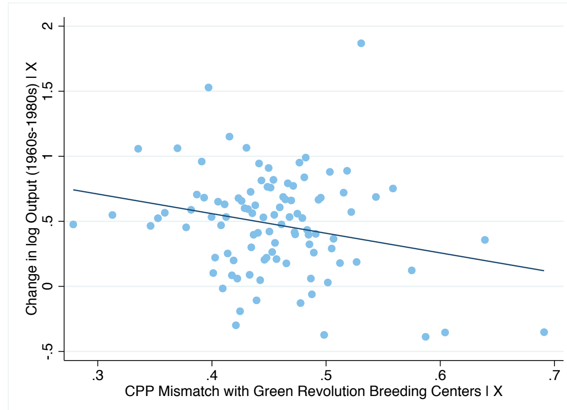
Our sample consists of the 8 crops in Table A11 intersected with the 85 low-income countries in the Evenson and Gollin (2003a,b) data.

Figure 4a displays the partial correlation plot corresponding to Equation 6.1. CPP mismatch with centers of Green Revolution breeding substantially reduced the adoption of HYVs. Our estimate implies that the 75th percentile crop-country pair had 5 percentage points lower HYV penetration than the 25th percentile in 1985, relative to a mean HYV penetration value of 5%. If we restrict attention to corn, wheat, and rice, the three most prominent Green Revolution crops, our coefficient estimate implies an 18 percentage point difference between the 75th and 25th percentiles relative to a mean of 14% (see Table A12). 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 ($p = 0.013$), indicating that our findings are truly driven by features of IARC ecology.

Figure 4: Inappropriateness and the Efficacy 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 $\text{CPPMismatchGR}_{k,\ell}$ and the dependent variable is listed at the top of each sub-figure. In Figure 4a, the dependent variable is the share of production using modern varieties in 1980 ($p = 0.006$) and in Figure 4b, 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.

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:

$$y_{k,\ell,1980s} - y_{k,\ell,1960s} = \beta \cdot \text{CPPMismatchGR}_{k,\ell} + \tau \cdot y_{k,\ell,1960s} + \chi_\ell + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \qquad (6.2)$$

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 the direct effects of time invariant ecology and local suitability, identifying how changes in output respond to changes in the geography of innovation, and hence inappropriateness.

Figure 4b reports the partial correlation plot corresponding to Equation 6.2. Production substantially shifted away, in relative terms, from crop-location pairs more ecologically mismatched with the IARCs. Table A13 documents that the relationship between CPPMismatchGR and production 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). These findings are consistent with a causal interpretation of the main result.

Taken together, our findings illustrate how ecological mismatch shaped the impact of the Green Revolution and, more broadly, how changes in the centers of innovation can shift the relationship between ecological conditions and productivity. Our findings illustrate systematically that the Green Revolution's focus on developing a small set of HYVs and distributing them widely may have undermined 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.

6.2 Technology Adoption in Sub-Saharan Africa

We next 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 geocoded 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 key dependent variable is farm-by-crop information on the use of improved seeds (i.e., not locally bred varieties). In total, we have data on approximately 120,000 crop-farm pairs across all eight countries.

Our main estimating equation is:

$$\text{ImprovedSeed}_{k,z} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell(z)} + \chi_{\ell(z)} + \chi_k + \varepsilon_{k,z} \tag{6.3}$$

where k continues to index crops and z indexes farms in the LSMS-ISA data. The dependent variable is an indicator that equals one if farmer z uses an improved seed variety for crop k. χ_k denote crop fixed effects and $\chi_{\ell(z)}$ denote 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

Table 4: CPP Mismach Inhibits Biotechnology Adoption in Africa

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is Improved Seed Use (=1)					
	Panel A: 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
	Panel B: 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
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 with the frontier is estimated as CPP mismatch with the US and in Panel B it is estimated using the frontier set selected from the UPOV data. 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.

important barrier to productivity enhancements in this setting.

Our findings are reported in Table 4, where CPP mismatch is measured either as CPP mismatch with the US (Panel A) or CPP mismatch with the measured set of crop-specific frontier countries (Panel B). 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), despite the ostensibly large market opportunity.

7. Inappropriate Technology and Productivity: Present and Future

We next use our empirical estimates, in combination with the model, to study how the inappropriateness of technology affects global productivity. We then study a series of counterfactual scenarios that model ongoing changes and policy opportunities in global biotechnology.

7.1 Methods

From Theory to Data. Our empirical findings about technology transfer in Section 4 and production distortions in Section 5 suggest that the observed world equilibrium is well-approximated with a structure of a few "leaders" driving the frontier of agricultural technology. In this subsection, we describe a simplification of our full model from Section 2 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" $F_k \in \{1, \dots, L\}$. In the Frontier producer of each crop k, 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 $\hat{\tau} > 0$.[25] These assumptions encode a fixed knowledge gap in productivity units for each crop, to match our empirical identification strategy. 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 each crop price p_k lies on the isoleastic demand curve

$$\frac{p_k}{\bar{p}_k} = \left(\frac{Y_k}{\bar{Y}_k}\right)^{-\varepsilon} \tag{7.1}$$

where $(\bar{p}_k, \bar{Y}_k)_{k=1}^K$ are constants, Y_k is total production of crop k in the world, and $\varepsilon > 0$ is an

[25]More 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.

elasticity of demand for each crop relative to a numeraire good representing the rest of the economy. Thus, international prices provide a hedge against lower productivity.

We now specialize the key model predictions about production and productivity, introduced in Proposition 2, to this case of the model. Let δ_{k,ℓ,F_k} denote CPP mismatch with the crop-specific frontier. Production of crop k in country ℓ is given by[26]

$$\log Y_{k,\ell} = -\eta\lambda\delta_{k,\ell,F_k} + \eta(\log p_k + \log \omega_{k,\ell} + \alpha\bar{A}_k + (1-\alpha)\bar{B}) - (\eta - 1)\log \Xi_\ell \tag{7.2}$$

where $\lambda := (1-\alpha)\hat{\tau} > 0$ is the sensitivity of log crop-specific productivity to CPP mismatch in the model and Ξ_ℓ is the productivity index

$$\log \Xi_\ell = \alpha \log \bar{A}_k + (1-\alpha)\log \bar{B} + \frac{1}{\eta}\log\left(\sum_{k=1}^{K} p_k^\eta \omega_{k,\ell}^\eta e^{-\eta\beta\delta_{k,\ell,F_k}}\right) \tag{7.3}$$

Comparing Equation 7.2 with the regression model Equation 5.2 reveals that our empirical estimate of β, the sensitivity of log output to CPP mismatch, identifies the (negative) product of the productivity effect λ and the elasticity of supply η. Equation 7.3 shows how, conditional on separately identifying (λ, η) and determining world prices from Equation 7.1, we can translate our estimates into total country-level revenue productivity.

Calibration. Our calibration is summarized in Table 5. 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.[27] Combining this estimate with our baseline estimate of $\beta = -7.14$ (Table 3, column 5) yields an estimate of $\lambda = 2.90$, in units of percent productivity loss per basis point of CPP mismatch.

Conditional on η, the crop-by-location productivity $\Theta_{k,\ell}$ is identified up to scale from data on planted area by crop, $\pi_{k,\ell}$. Mirroring our analysis in Section 5, 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

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

[27]These authors estimate, in a nutshell, is the plot-level 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 5.2	Effect of CPPMismatchFrontier on output
η	2.46	Costinot et al. (2016)	Elasticity of supply to productivity
ε	0.35	Muhammad et al. (2011)	Price elasticity of global food demand
$\pi_{k,\ell}$	—	FAOSTAT Database	Planted area for each crop in each country
Ξ_ℓ	—	Fuglie (2012, 2015)	Baseline revenue productivity by country

and hence pin down the scale of local innate productivity and prices. Finally, to calibrate the crop-level demand curves, we use the average value estimated by the US Department of Agriculture for the (compensated) own-price elasticity of global food consumption (Muhammad et al., 2011). This yields $\varepsilon = 0.35$.[28]

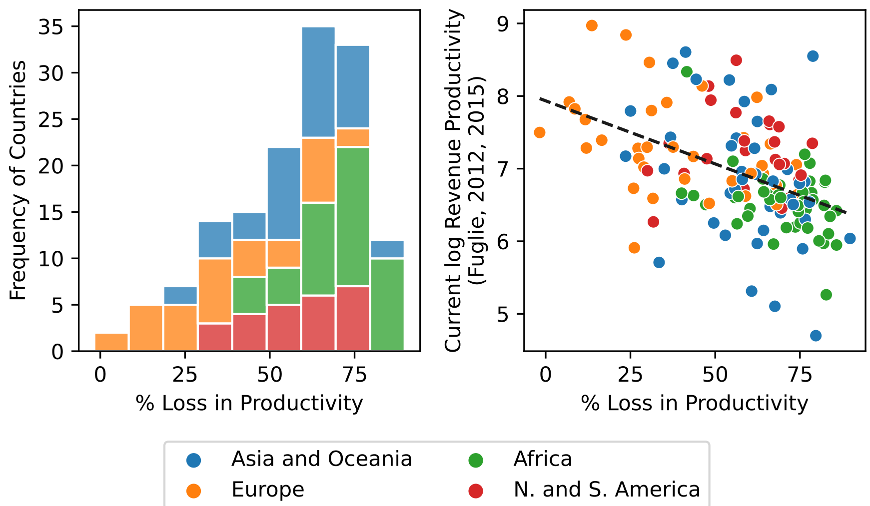
7.2 The Productivity Effects of Inappropriateness

We first define and study a counterfactual in which "inappropriateness is removed." We make no claim that such an intervention is optimal in the model under a natural welfare criterion; however, it provides a benchmark for the total effect of the "inappropriate technology bias" on global productivity. 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. In terms of primitives, this intervention removes the knowledge gap between frontier and non-frontier CPP research; more concretely, it is equivalent to reducing all CPP mismatch to zero. 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 key statistics: the global average revenue productivity change and the percent change in the 75-25 percentile gap (inter-quartile range) of log revenue productivity.

We find that inappropriateness reduces global productivity by 42.2% and explains 15.1% of global disparities, as captured by the IQR (see Table A15). Figure 5 explores the distributional implications of our findings. The left panel displays the distribution of productivity losses across continents, and shows that the largest losses from inappropriateness are concentrated in Africa and Asia, while the smallest are in Europe. The right panel documents a negative relationship ($p < 0.01$) between our estimated productivity losses and present-

[28]Specifically, we use the average of the "low," "middle," and "high" income estimates in Appendix Table 3 of that publication.

Figure 5: 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 dashed line is a best-fit linear regression across countries (coef. = −0.017, t = −6.2). In each plot, colors indicate continents.

day revenue productivity.[29] Thus, inappropriateness has the largest negative effects on productivity in precisely the countries that are least productive today.

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. Our empirical analysis is focused on accurately estimating β, the effect of CPP mismatch on output. In order to estimate the aggregate effects of inappropriateness, we also rely on two additional parameters that we obtain from existing literature, the elasticity of supply to productivity (η) and the price elasticity of demand (ε). 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 A5).[30] As expected, reducing price impacts (increasing ε) dampens the effects

[29]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 -0.014 ($p < 0.01$).

[30]For the maximum and minimum plausible values for ε, we use the maximum and minimum price elasticities reported in Muhammad et al. (2011). For the minimum plausible value for η, we use $\eta = 2$ which

of inappropriateness, while decreasing the extent of unobserved heterogeneity (decreasing η) amplifies them; nevertheless, the findings are broadly very similar.

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 3.4, 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 A6 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 increases our estimate of the losses due to inappropriateness to 52%, and increases the effect on disparities in productivity to 16%.

7.3 Mapping a Second Green Revolution

Next, we turn to a series of counterfactual exercises that capture real-world policy decisions or trends in global biotechnology. Our first exercise, in the spirit of the historical Green Revolution, is to study how to target a modern "Second Green Revolution." If the Rockefeller Foundation and other philanthropic groups were to design the Green Revolution today, with benefits that could be shared as widely as possible, where should they locate the main research centers? 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.

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 lcoations. Our results also suggest potentially large opportunities for emerging markets like Brazil, Russia, India, and China to market their technology around the world.

is slightly lower than the estimate of $\eta = 2.06$ in Sotelo (2020), to our knowledge the lowest estimate of the relevant parameter in existing literature. For the maximum plausible value, we add the difference between the Sotelo (2020) estimate and our baseline estimate of η.

Table 6: Inappropriateness-Minimizing Centers for Modern Agricultural Innovation

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sites Chosen to Minimize Global Inappropriateness				Sites Chosen to Minimize Inappropriateness in Countries with Below Median Productivity			
Crop	Best Site	% Change in Productivity	Second Best Site	% Change in Productivity	Best Site	% Change in Productivity	Second Best Site	% Change in Productivity
Wheat	China	3.29	India	1.87	India	10.42	Pakistan	6.97
Maize	China	8.50	USA	6.16	Nigeria	9.26	Tanzania	7.46
Sorghum	India	0.83	Nigeria	0.76	Nigeria	3.10	India	2.71
Millet	Nigeria	0.90	India	0.68	Nigeria	2.97	Zimbabwe	1.76
Beans	India	1.30	Brazil	1.13	India	3.25	Tanzania	1.41
Potatoes	China	0.97	India	0.48	India	0.94	Russia	0.52
Cassava	Nigeria	0.41	Ghana	0.31	Nigeria	1.60	DRC	1.33
Rice	China	7.55	India	6.53	India	13.32	Thailand	8.65

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.

7.4 New Biotechnological Leaders

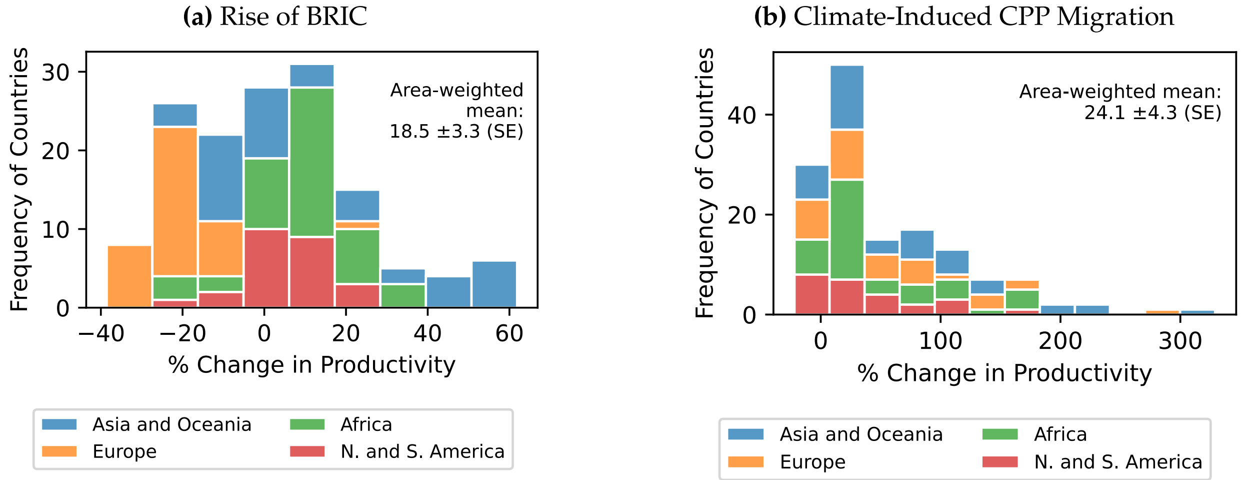
We now study the impact of the rise of Brazil, Russia, India, and China (BRIC) as growing players in agricultural technology development. To highlight the recent growth of the BRIC countries, Figure A7 displays the number of patented agricultural technologies in the US and in the BRIC countries over 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 Brazil, Russia, 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.[31]

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:

$$\text{CPPMismatchFrontier}^{\text{BRIC}}_{k,\ell} = \sum_{\ell' \in \text{BRIC}} \frac{\pi_{\ell',k}}{\sum_{\ell'' \in \text{BRIC}} \pi_{\ell'',k}} \times \text{CPPMismatch}_{k,\ell,\ell'} \tag{7.4}$$

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

Figure 6: Counterfactuals: Rise of BRIC and Climate-Induced CPP Migration



Notes: Each graph is a histogram of productivity changes, across countries, in the labeled scenario.

In words, we estimate the inappropriateness of BRIC ecology for each crop, weighting by area $\pi_{k,\ell}$.[32] We then consider the effects of moving the frontier such that $\delta_{k,\ell,F_k} = \text{CPPMismatchFrontier}^{\text{BRIC}}_{k,\ell}$.

Figure 6a summarizes our findings in a continent-coded histogram of the revenue productivity changes. The average effect is a 18.5% productivity boost, due to the fact that the BRIC countries span more ecological diversity than the existing technological leaders. Africa stands 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 purely local technological development.

7.5 Ecological Differences Under CPP Mass Migration

So far, we have treated ecology as immutable and allowed innovation to move around the world. But climate change may alter ecological systems over the coming decades (Parmesan and Yohe, 2003). In the context of CPPs, increases in temperature are predicted to generate

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

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.[33] This could change the relevant "geography of innovation" by shifting the relevant set of CPP threats in each country, even if the identity of innovating countries remains fixed.

To investigate the impact of climate change on the 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.[34] We then use these data to construct $\text{CPPDistFrontier}^{CC}_{k,\ell}$ based on ecological dissimilarity to the modern set of frontier innovators, and re-calculate productivity as in the previous counterfactuals.

Figure 6b 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.

8. 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 mis-

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

[34] 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.

match 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, changes in the geography of innovation can have large effects on 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. We argue that, in the future, changes in the centers of innovation and in ecology could have similarly large but unequal productivity effects. 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

A. Omitted Proofs and Derivations

We first derive lemmas that underpin our definition of equilibrium (Definition 1) and assist in proving the main results, Propositions 1 and 2. We then prove the main results.

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*

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

Moreover, in equilibrium, farmers' crop and technology choice solves

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

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

$$\Pi_{k,\ell',i} = \max_{X_{k,\ell',\ell}} \left\{ p_k (X_{k,\ell',i})^{1-\gamma} (\theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i})^{\gamma} - q_{k,\ell',\ell} X_{k,\ell',\ell} \right\} \tag{A.3}$$

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

$$0 = (1-\gamma) p_k (\theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i})^{\gamma} (X_{k,\ell',i})^{-\gamma} - q_{k,\ell',\ell} \tag{A.4}$$

Or $X_{k,\ell' i} = (1-\gamma)^{\frac{1}{\gamma}} q_{k,\ell',\ell}^{-\frac{1}{\gamma}} p_k^{\frac{1}{\gamma}} (\theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i})$. Substituting this into Equation A.3,

$$\Pi_{k,\ell',i} = \gamma \cdot R_{k,\ell,i} = \gamma \cdot \left(p_k^{\frac{1}{\gamma}} \left(\frac{1-\gamma}{q_{k,\ell',\ell}} \right)^{\frac{1-\gamma}{\gamma}} \theta_{k,\ell',\ell} \omega_{k,\ell} \varepsilon_{k,\ell',i} \right) \tag{A.5}$$

where $R_{k,\ell,i}$ is defined as the farmer's revenue before factor payments. Finally, to derive Equation A.2, we note that farmers maximize $\Pi_{k,\ell',i}$ and that $q_{k,\ell'\ell} = 1-\gamma$ in equilibrium according to Lemma 3. □

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

$$\pi_{k,\ell',\ell} = \frac{p_k^{\frac{\eta}{\gamma}} \theta_{k,\ell',\ell}^{\eta} \omega_{k,\ell}^{\eta}}{\sum_{k',\ell''} p_{k'}^{\frac{\eta}{\gamma}} \theta_{k',\ell'',\ell}^{\eta} \omega_{k',\ell}^{\eta}} \tag{A.6}$$

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

$$\tilde{\Xi}_{\ell} = \gamma \left(\sum_{k=1}^{K} \sum_{\ell'=1}^{L} p_k^{\frac{\eta}{\gamma}} \theta_{k,\ell',\ell}^{\eta} \omega_{k,\ell}^{\eta} \right)^{\frac{1}{\eta}} \tag{A.7}$$

Proof. Let $u_i^* \in \{1,\ldots,K\} \times \{1,\ldots,L\}$ denote the crop-technology choice of farmer i, let $\nu_{k,\ell',\ell} = (1-\gamma)p_k^{1/\gamma}\omega_{k,\ell}\theta_{k,\ell',\ell}$ 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 $\pi_{k,\ell',\ell}$:

$$\begin{aligned} \pi_{k,\ell',\ell} &= \int_0^{\infty} \prod_{k',\ell'' \neq k,\ell'} F\left(\frac{\nu_{k,\ell',\ell}}{\nu_{k',\ell'',\ell}} z\right) \mathrm{d}F(z) \\ &= \int_0^{\infty} \exp\left(-z^{-\eta} \frac{\tilde{\Xi}_{\ell}^{\eta}}{\nu_{k,\ell',\ell}^{\eta}}\right) z^{-1-\eta}\, \mathrm{d}z \end{aligned} \tag{A.8}$$

Where, in the second line, we substituted the expression for $F(z)$, simplified, and defined the productivity index

$$\tilde{\Xi}_\ell = \left(\sum_{k=1}^{K}\sum_{\ell'=1}^{L} \nu_{k,\ell',\ell}^{\eta}\right)^{\frac{1}{\eta}} \tag{A.9}$$

See that, after a change in variables in the integrand to $\tilde{z} = z\frac{\nu_{k,\ell',\ell}}{\tilde{\Xi}_\ell}$, that the original integral can be re-written and simplified as

$$\begin{aligned}\pi_{k,\ell',\ell} &= \frac{\nu_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''}\nu_{k',\ell'',\ell}^{\eta}}\int_0^\infty \exp\left(-\tilde{z}^{-\eta}\right)\tilde{z}^{-1-\eta}\,\mathrm{d}z \\ &= \frac{\nu_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''}\nu_{k',\ell'',\ell}^{\eta}}\int_0^\infty \mathrm{d}F(\tilde{z}) = \frac{\nu_{k,\ell',\ell}^{\eta}}{\sum_{k',\ell''}\nu_{k',\ell'',\ell}^{\eta}}\end{aligned} \tag{A.10}$$

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

$$V_i^* = \max_{k',\ell''}\{\nu_{k',\ell'',\ell}\varepsilon_{k',\ell'',i}\} \tag{A.11}$$

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 A.8 up to the realization $\frac{v}{s\nu(k',\ell'',\ell)^\eta}$, and normalizing by the probability of choosing (k',ℓ''):

$$\mathbb{P}[V_i^* \le v \mid u_i^* = (k',\ell'')] = \frac{1}{\pi_{k,\ell',\ell}}\int_0^{\frac{v}{s\nu_{k',\ell'',\ell}^{\eta}}} F\left(\frac{\nu_{k,\ell',\ell}^{\eta}}{\nu_{k',\ell'',\ell}^{\eta}}z\right)\mathrm{d}F(z) \tag{A.12}$$

After the change in variables in the integrand to $\tilde{z} = z\frac{\nu_{k,\ell',\ell}}{\tilde{\Xi}_\ell}$, see that we can write

$$\mathbb{P}[V_i^* \le v \mid u_i^* = (k',\ell'')] = \int_0^{\frac{v}{s\tilde{\Xi}_\ell}} \mathrm{d}F\left(\tilde{z}\right) \tag{A.13}$$

which implies that V_i^*, conditional on $u_i^* = (k',\ell'')$, can be written as the product of $\tilde{\Xi}_\ell$ 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^*. Moreover, it implies that $\mathbb{E}[V_i^*|u_i^* = (k',\ell'')] = \tilde{\Xi}_\ell$ for any (k',ℓ'') as desired. Moreover, the total profits of all farmers planting (k,ℓ') is

$\pi_{k,\ell',\ell}\mathbb{E}[V_i^*|u_i^* = (k', \ell'')] = \pi_{k,\ell',\ell}\tilde{\Xi}_\ell.$

$\square$

Lemma 3. *The innovator in country ℓ' charges price $q_{k,\ell',\ell} = 1-\gamma$ for its (k,ℓ) technology. Moreover, each innovator's research in (k,ℓ) specific technology solves the following problem*

$$\max_{(B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}} \left\{ \frac{(1-\gamma)}{\exp(\rho_{\ell',\ell})}\hat{\Xi}_\ell^{1-\eta}\hat{p}_k^{\frac{\eta}{\gamma}}\omega_{k,\ell}^{\eta}A_{k,\ell'}^{\alpha\eta}\prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} - \sum_{t\in\mathcal{T}_{k,\ell}}\exp\Big(-\tau(\hat{B}_{t,k,\ell',\ell'})\Big)\frac{(B_{0,\ell'}B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)}\right\} \tag{A.14}$$

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. We first show that $q_{k,\ell',\ell} = 1-\gamma$. Conditional on a choice for quality $\theta_{k,\ell',\ell}$, the monopolist chooses its price to solve

$$\max_{q_{k,\ell',\ell}} \left\{\int_0^1 (q_{k,\ell',\ell} - c_{k,\ell',\ell})\cdot X_{k,\ell',i}\cdot \mathbb{I}[u^*(i) = (k,\ell')]\,\mathrm{d}i\right\} \tag{A.15}$$

where $c_{k,\ell',\ell}$ is the marginal cost; $X_{k,\ell',i}$ 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

$$\max_{q_{k,\ell',\ell}} \left\{\left((1-\gamma)^{\frac{1}{\gamma}}p_k^{\frac{1}{\gamma}}(\theta_{k,\ell',\ell}\omega_{k,\ell})\pi_{k,\ell',\ell}f(\Xi_\ell)\right)(q_{k,\ell',\ell}-c_{k,\ell',\ell})\,q_{k,\ell',\ell}^{-\frac{1}{\gamma}}\right\} \tag{A.16}$$

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 A.16 is concave. Taking the first order condition and re-arranging gives $q_{k,\ell',\ell} = \frac{c_{k,\ell',\ell}}{1-\gamma}$. Taking $c_{k,\ell',\ell} = (1-\gamma)^2$ proves that $q_{k,\ell',\ell} = 1-\gamma$.

We next derive the innovator's problem for choosing the $B_{t,k,\ell',\ell}$. Let $V_{k,\ell',\ell}$ be the total profit of farmers in ℓ who choose (k,ℓ'). As shown in Lemma 2, $V_{k,\ell',\ell} = \pi_{k,\ell',\ell}\Xi_\ell$. Using the expression for $\pi_{k,\ell',\ell}$ from Lemma 2, we can re-write in terms of research levels, prices, innate productivities, and total productivity as

$$V((B_{t,k,\ell',\ell})_{t\in\mathcal{T}_{k,\ell}}; p_k, \omega_{k,\ell}, A_{k,\ell'}\Xi_\ell) = \gamma \Xi_\ell^{1-\eta} p_k^{\frac{\eta}{\gamma}} \omega_{k,\ell}^{\eta} A_{k,\ell'}^{\alpha\eta} \prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} \tag{A.17}$$

Observe finally that 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). Finally, innovators receive fraction $e^{-\rho_{\ell',\ell}} \leq 1$ of this revenue. Thus, the innovator's objective is

$$\sum_{k,\ell}\left[\frac{(1-\gamma)}{\exp(\rho_{\ell',\ell})}\hat{\Xi}_\ell^{1-\eta}\hat{p}_k^{\frac{\eta}{\gamma}}\omega_{k,\ell}^{\eta}A_{k,\ell'}^{\alpha\eta}\prod_{t\in\mathcal{T}_{k,\ell}} B_{t,k,\ell',\ell}^{\frac{\eta(1-\alpha)}{T}} - \sum_{t\in\mathcal{T}_{k,\ell}}\exp\Big(-\tau(\hat{B}_{t,k,\ell',\ell'})\Big)\frac{(B_{0,\ell'}B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)}\right] \tag{A.18}$$

given conjectures $(\hat{p}_k, \hat{\Xi}_\ell)$ for endogenous revenue productivity in each country ℓ and prices of each crop k and conjecture $(\hat{B}_{t,k,\ell',\ell'})$ for local research on each pest. We obtain the desired form by noting that the problem is linearly separable for each (k,ℓ), and the optimization problem can be solved separately for each (k,ℓ).

□

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 A.14, derived in Lemma 3, is concave under the maintained assumption that $\eta(1-\alpha) < 1+\phi$ (Footnote 9). 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

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

We next take logs, impose the equilibrium condition that the conjectures are correct, and substitute in the definition of $\theta_{k,\ell',\ell}$. The first-order condition re-arranges to

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

We next substitute Equation A.2 into the definition of $\log\theta_{k,\ell',\ell}$ (Equation 2.3) to write

$$\log\theta_{k,\ell',\ell} = \alpha\log A_{k,\ell'} + (1-\alpha)\frac{\log((1-\gamma)\eta(1-\alpha))}{1+\phi} - (1-\alpha)B_{0,\ell'} - \frac{(1-\alpha)\rho_{\ell',\ell}}{1+\phi} + \frac{(1-\alpha)(\eta-1)}{1+\phi}\log\Xi_\ell + \frac{(1-\alpha)\eta}{\gamma(1+\phi)}\log p_k + \frac{(1-\alpha)\eta}{1+\phi}\log\omega_{k,\ell} + \frac{(1-\alpha)\eta}{1+\phi}\log\theta_{k,\ell',\ell} + \frac{1-\alpha}{(1+\phi)T}\sum_{\tau\in\mathcal{T}_{k,\ell}}\tau(B_{t,k,\ell',\ell'})$$

We now simplify the last term on the right-hand-side. Observe that, for any $t\in\mathcal{T}_{k,\ell'}$ or "locally present pest," the conjectured solution $B_{t,k,\ell',\ell'}>0$ to Equation A.2. Denote this as $B_{k,\ell'}$. Next, for any $t\notin\mathcal{T}_{k,\ell'}$, $B_{t,k,\ell',\ell'}=0$ 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

$$\frac{1-\alpha}{(1+\phi)T}\sum_{\tau\in\mathcal{T}_{k,\ell}}\tau(B_{t,k,\ell',\ell'}) = \frac{1-\alpha}{1+\phi}(1-\delta_{k,\ell',\ell})B_{k,\ell'} + 0\cdot\delta_{k,\ell',\ell} = \frac{1-\alpha}{1+\phi}(1-\delta_{k,\ell',\ell})B_{k,\ell'} \tag{A.19}$$

We finally derive the desired expression for technology transfer. As show in Lemma 3 (Equation A.17), total expenditure on the technological input is

$$E_{k,\ell',\ell} := (1-\gamma)\Xi_\ell^{1-\eta}p_k^{\frac{\eta}{\gamma}}\omega_{k,\ell}^{\eta}\theta_{k,\ell',\ell}^{\eta} \tag{A.20}$$

Since the price is $q_{k,\ell',\ell}=1-\gamma$ (Lemma 3), the total quantity demanded is $X_{k,\ell',\ell}=E_{k,\ell',\ell}/(1-\gamma)$. Finally, taking logs and substituting in Equations A.2 and A.19, we write

$$\log X_{k,\ell',\ell} = \beta_{k,\ell'}\cdot\delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell,\ell'} \tag{A.21}$$

where the coefficient is

$$\beta_{k,\ell'} = -\frac{\eta(1-\alpha)\tau(B_{k,\ell'})}{1+\phi-\eta(1-\alpha)} \tag{A.22}$$

and the fixed effects can be written as

$$\begin{aligned}
\chi_{k,\ell} &= \frac{\left(\frac{1}{\gamma}\log p_k + (1-\alpha)\eta\log\omega_{k,\ell} + (1-\alpha)(\eta-1)\log\Xi_\ell\right)}{1+\phi-\eta(1-\alpha)} + (1-\eta)\log\Xi_\ell + \frac{\eta}{\gamma}\log p_k + \eta\log\omega_{k,\ell}\\
\chi_{k,\ell'} &= \frac{\left(\alpha\log A_{k,\ell'} - (1-\alpha)B_{0,\ell'} + (1-\alpha)\log((1-\gamma)\eta(1-\alpha))\right)}{1+\phi-\eta(1-\alpha)}\\
\chi_{\ell',\ell} &= \frac{-(1-\alpha)\rho_{\ell,\ell'}}{1+\phi-\eta(1-\alpha)} + \log(1-\gamma)
\end{aligned} \tag{A.23}$$

A.3 Proof of Proposition 2

As derived in Lemma 1, physical production on farm i conditional on planting (k, ℓ') is $p_k^{1/\gamma-1}\theta_{k,\ell',\ell}\omega_{k,\ell}\varepsilon_{k,\ell',i}$, or 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':

$$Y_{k,\ell} = \sum_{\ell'}^{L} \mathbb{E}\left[\frac{V_i^*}{\gamma p_k} \mid u_i^* = (k, \ell')\right] \cdot \pi_{k,\ell',\ell} \tag{A.24}$$

As shown in Lemma 2, $\mathbb{E}\left[V_i^* = u_i^* = (k, \ell')\right] = \tilde{\Xi}_\ell$ for any (k, ℓ'). Define $\Xi_\ell = \tilde{\Xi}_\ell/\gamma$ as a revenue productivity index, which agrees with the definition in Equation 2.8. By the arguments above, $\mathbb{E}\left[\frac{V_i^*}{\gamma p_k} \mid u_i^* = (k, \ell')\right] \equiv \frac{\Xi_\ell}{p_k}$, or the uniform physical yield. Combining this with the planted area result of Lemma 2, taking a log, and defining $\Theta_{k,\ell}$ as in Equation 2.8, yields

$$\log Y_{k,\ell} = \eta \log \Theta_{k,\ell} + \eta \log \omega_{k,\ell} + (\eta - 1) \log p_k + (1 - \eta) \log \Xi_\ell \tag{A.25}$$

This proves the stated claim of Proposition 2. As additional results, we derive analogous expressions for planted area and physical yield. First, see that 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

$$\log \pi_{k,\ell} = \eta \log \Theta_{k,\ell} + \eta \log \omega_{k,\ell} + \eta \log p_k - \eta \log \Xi_\ell \tag{A.26}$$

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

$$\log z_{k,\ell} = \log Y_{k,\ell} - \log \pi_{k,\ell} = \log \Xi_\ell - \log p_k \tag{A.27}$$

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 3.1). 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.[35] 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 A14. We show results corresponding to our analyses of international technology diffusion (columns 1-3), production (column 4), and technology adoption (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 suggest 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.

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

B.2.1 Constructing Agro-climatic Mismatch

We include ten key agroclimatic 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.[36] 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).[37] We then compute the value of each characteristic for each crop-by-country pair by estimating the average value of each characteristic in each country on the land devoted to the crop in question; we denote these as $x_{k,\ell}$. We then normalize each characteristic to comparable, z-score units by re-centering by the global mean value of each attribute and normalizing by the global dispersion (standard deviation); we refer to these normalized values as $\hat{x}_{k,\ell}$. Then, for each agro-climatic characteristic x, crop, and location pair, we define the absolute distances

$$\Delta\hat{x}_{k,\ell,\ell'} = |\hat{x}_{k,\ell} - \hat{x}_{k,\ell'}| \tag{B.1}$$

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 $\mathcal{X}$:[38]

$$\text{AgroClimMismatch}_{k,\ell,\ell'} = \frac{1}{|\mathcal{X}|} \cdot \sum_{x \in \mathcal{X}} \Delta\hat{x}_{k,\ell,\ell'} \tag{B.2}$$

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 B1 re-produces our baseline estimate of Equation 4.1, our main technology transfer model, on the sample of

[36] 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`).

[37] 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.

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

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 B2, we present our results for production. The dependent variable is log of agricultural output and the regression specification is (5.2). 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 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 B3 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 B2. Our modeling strategy is identical to the one outlined in Section 7.1 of the main text. We find that inappropriateness, as captured by both CPP mismatch and agro-climatic mismatch, reduces global productivity by 52% and increases disparities in global productivity across countries, measured by the interquartile range, by 16%. These results are summarized graphically in Figure A6, which is structured in the same way as Figure 5. 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 B2, 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 2.1.3. 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 (UPOV PLUTO), 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:

$$\ln(V_k) = \alpha + \delta_1 \cdot \log \text{Area}_k + \delta_2 \cdot \log \text{GDPArea}_k + \delta_3 \cdot \log \text{IPArea}_k + \varepsilon_k \tag{B.3}$$

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:[39]

$$\log \text{GDPArea}_k = \log\left(\sum_{\ell} \text{Area}_{k,\ell} \cdot \text{GDP}_\ell\right) \qquad \log \text{IPArea}_k = \log\left(\sum_{\ell} \text{Area}_{k,\ell} \cdot \mathbb{I}_{\ell}^{IP}\right) \quad \text{(B.4)}$$

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 B1 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:

$$\log(V_{k,\ell}) = \delta_0 \log \text{Area}_{k,\ell} + \delta_1 \log \text{Area}_k + \delta_2 \log \text{GDPArea}_k + \delta_3 \log \text{IPArea}_k + \chi_\ell + \varepsilon_{k,\ell} \quad \text{(B.5)}$$

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 (B.5) are reported in Table B4. 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 estimates mirror our findings using the CPP-specific patent data

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

in Section 3.3 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 A2). 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 (4.1):

$$y_{k,\ell} = \beta \cdot \text{CPPMismatchFrontier}_{k,\ell} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \tag{B.6}$$

where $\text{CPPMismatchFrontier}_{k,\ell}$ is defined using either method described in Section 5.1. We expect CPP mismatch with the frontier to inhibit technology transfer; that is, we hypothesize that $\beta < 0$. Estimates of Equation B.6 are reported in Figure B3. 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 Growth of US Biotechnology

Since the 1990s, the US agricultural biotechnology sector has produced a growing share of global innovation, likely driven by the advent and increased use of genetic modification. Figure B4 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.

We investigate whether this shift in the geography of research affected the global distribution of production by disproportionately favoring producers in places where US technology—as opposed to European technology—was appropriate. For each country-crop pair, we measure the change in production between the 1990s and 2010s, and estimate:

$$\Delta \log y_{k,\ell}^{10-90} = \beta_1 \cdot \text{CPP Mismatch}_{k,\ell}^{US} + \beta_2 \cdot \text{CPP Mismatch}_{k,\ell}^{EU} + \gamma \cdot \log y_{k,\ell}^{1990} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \quad \text{(B.7)}$$

Our first hypothesis is that $\beta_1 < 0$, capturing the effect of the rise of the US on production in places where US technology is more or less appropriate. Our second hypothesis is that $\beta_1 < \beta_2$, capturing the fact that since 1990, US technology has grown substantially more than European technology, so we would expect CPP mismatch with the US to be a more important determinant of productivity changes than CPP mismatch with Europe.

Estimates of (B.7) are reported in Table B5, and across specifications we find evidence of both hypotheses. $\beta_1 < 0$ and β_2 is close to zero and positive in all specifications. These estimates are less precise than our main results, and β_1 is statistically distinguishable from β_2 in just one of the four specifications. Nevertheless, dovetailing with Section 6.1, these findings suggest that global productivity differences are endogenous to the evolving landscape of technology development. Geography does not have a fixed impact on development, but changing effects that can be shaped by the focus and direction of innovation.

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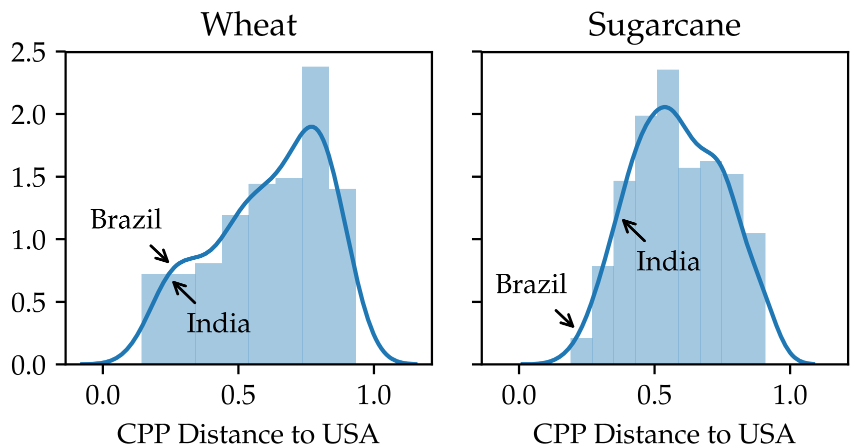
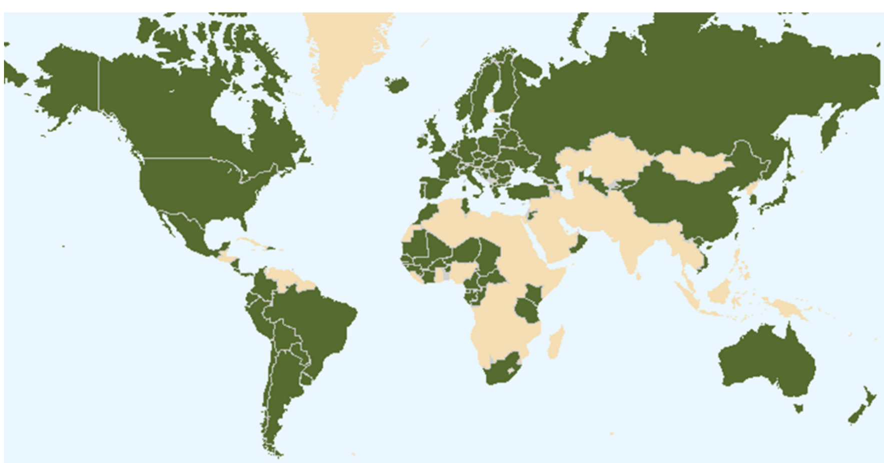
C. Supplemental Figures and Tables

Figure A1: 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 and Brazil are labeled.

Figure A2: UPOV Compliant Countries

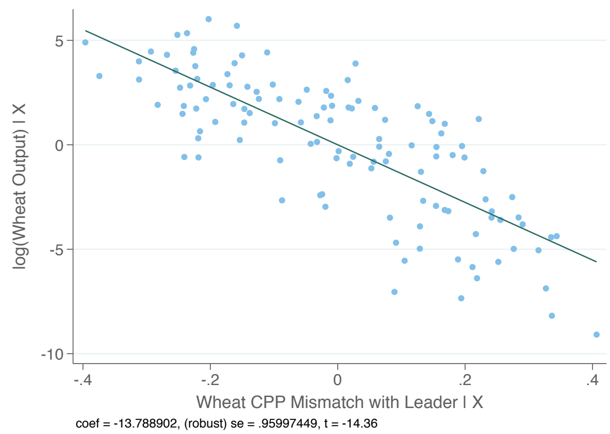


Notes: This figure denotes in green all UPOV member countries. This is the sample of countries for which we have data on biotechnology development and transfer.

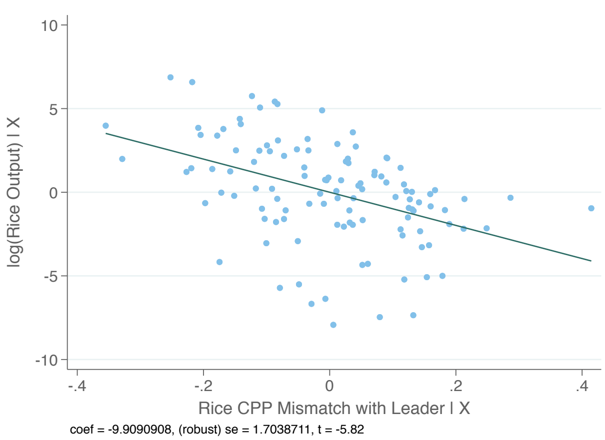
Figure A3: CPP Mismatch and Agricultural Output: Large Crops

(a) Corn

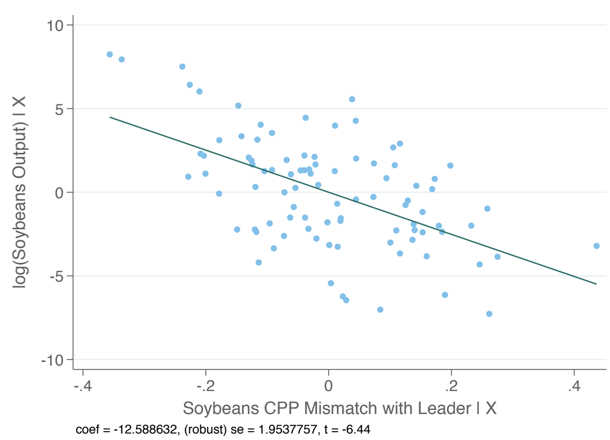
(b) Wheat



(c) Rice



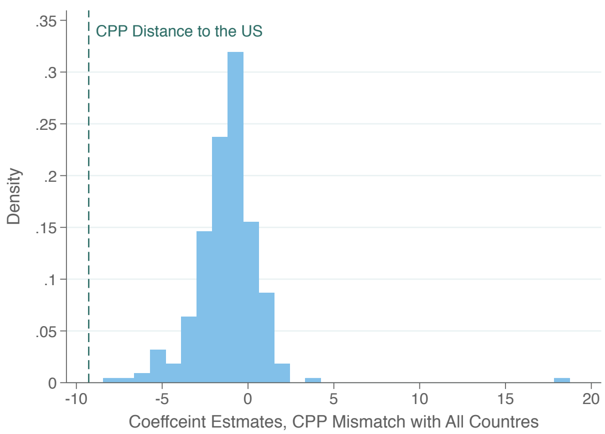
(d) Soybeans



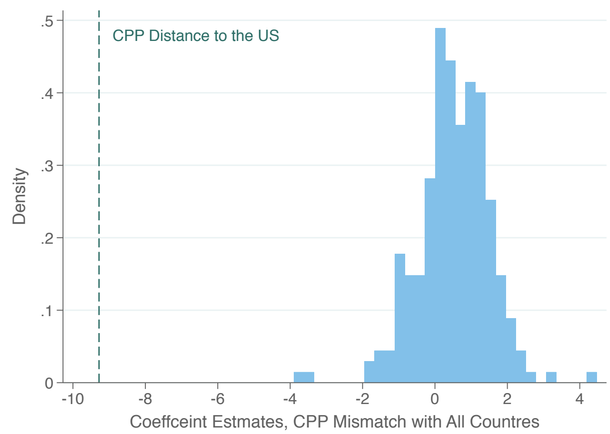
Notes: Each sub-figure reports a partial correlation plot of an estimate of (5.2) in which we restrict the sample to a single crop: corn, wheat, rice, and soybeans in A3a - A3d respectively. CPP mismatch is measured using the version in which we allow technological leadership to vary across crops. The coefficient estimates and standard errors are noted at the bottom of each sub-figure.

Figure A4: Falsification Test: CPP Mismatch with All Countries

(a) Unconditional



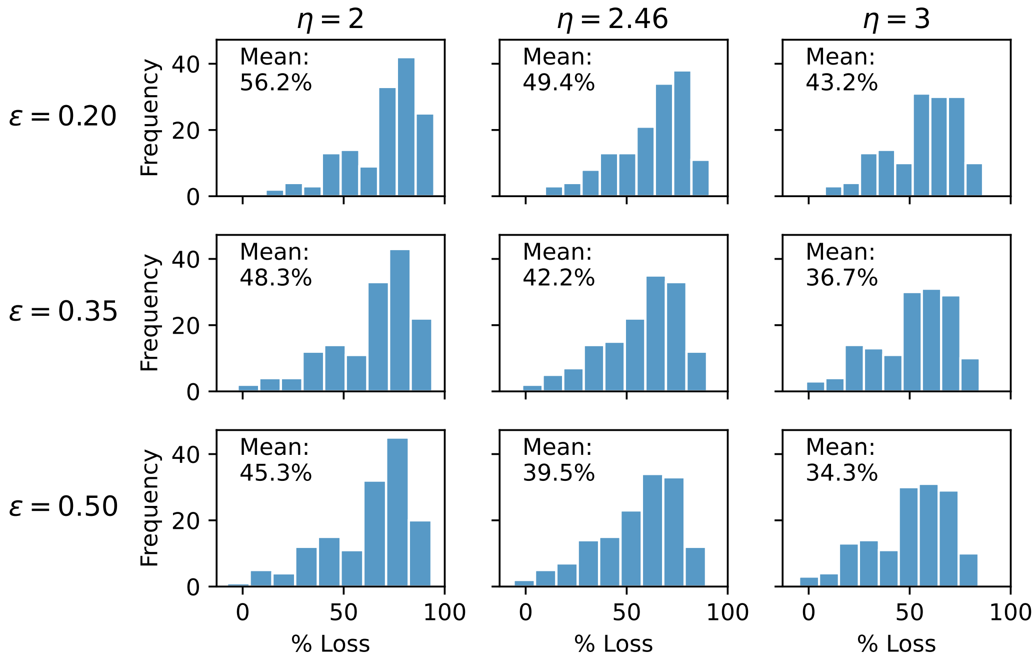
(b) Conditional on CPP Distance to the US



Notes: This figure displays histograms of the coefficient estimates of the relationship between CPP distance to each country separately and log of crop-level output. In A4a, CPP distance to each country is included on the right hand side of the regression alone (along with crop and country fixed effects) and A4b, CPP distance to the US is also included in the regression.

Figure A5: Sensitivity Analysis of Counterfactual Experiment

(a) Losses by Country



(b) Losses vs. Observed Productivity

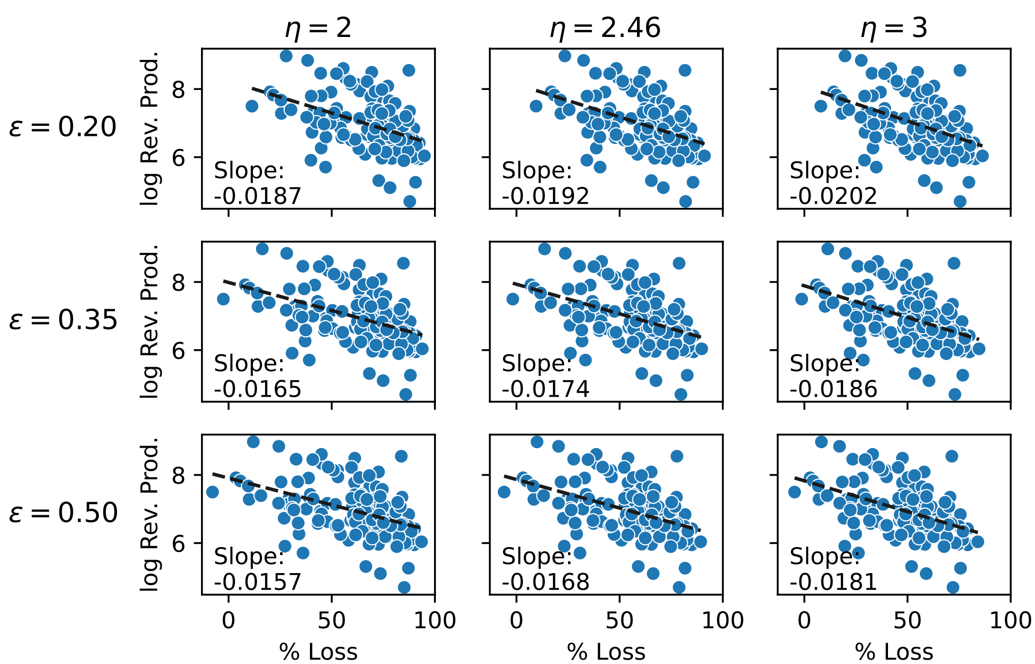
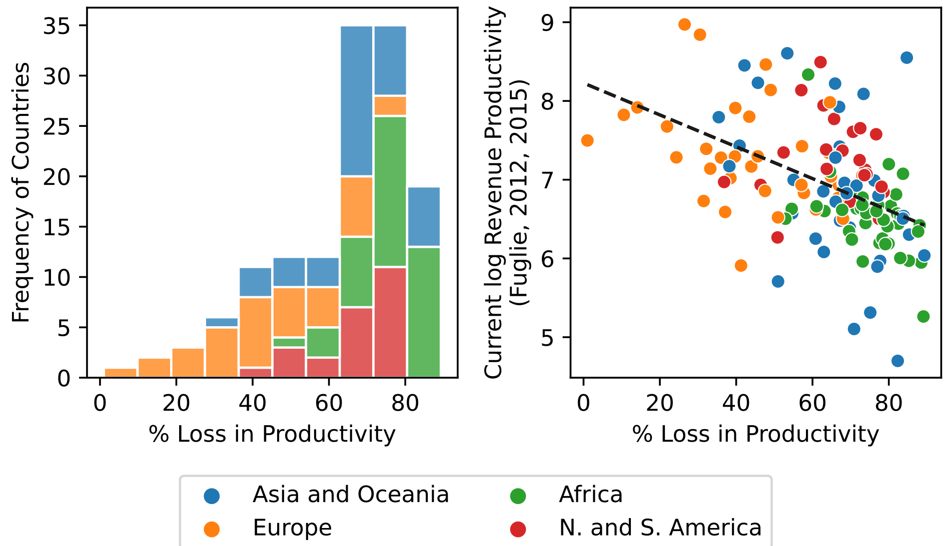
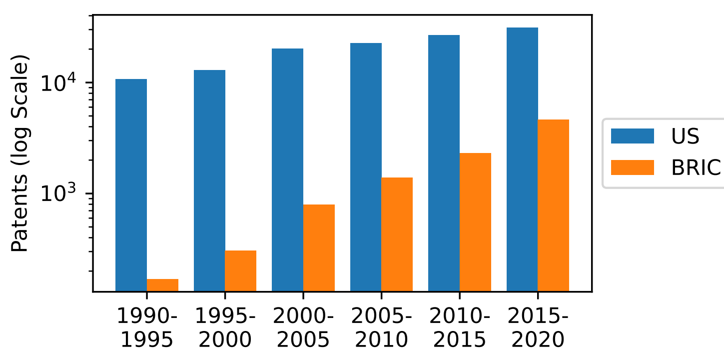


Figure A6: Causal Effects of Inappropriateness: CPP and Agro-Climatic Mismatch



Notes: This figure recreates Figure 5 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. The right graph is a scatterplot of productivity losses against observed productivity. The dashed line is a best-fit linear regression across countries. In each plot, colors indicate continents.

Figure A7: Growth in Agricultural Patented 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: Patenting Activity Directed Toward Local CPPs

	(1)	(2)	(3)
	CPP-Specific Patents (asinh)	Any CPP-Specific Patent (0/1)	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 A2: 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 A3: 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 bilaterial crop-level trade				✓			
Control for log bilaterial 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 A4: 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 A5: CPP Mismatch Reduces Area Harvested

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Area Harvested							
	CPP Mismatch with the US				CPP Mismatch with the Estimated Frontier			
CPP Mismatch (0-1)	-9.517***	-12.08***	-9.541***	-7.855***	-7.139***	-7.020***	-7.200***	-5.837***
	(1.212)	(2.892)	(0.595)	(0.635)	(0.941)	(0.725)	(0.437)	(0.496)
log(FAO-GAEZ-Predicted Output)		0.303***				0.363***		
		(0.0768)				(0.0487)		
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	6,675	2,268	6,683	5,908	6,469	2,268	6,474	5,748
R-squared	0.612	0.612			0.609	0.603		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP mismatch with the US and columns 5-8 use CPP mismatch with the estimated set of technological leader countries. 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 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 state and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A6: 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 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
	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
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. 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 A7: 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 A8: CPP Mismach Reduces Output: Crop × Continent Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Mismatch with the US				CPP Mismatch with the Estimated Frontier			
CPP Mismatch (0-1)	-8.809***	-9.831***	-8.780***	-8.198***	-8.780***	-8.198***	-6.999***	-6.385***
	(1.124)	(2.608)	(0.769)	(0.742)	(0.769)	(0.742)	(0.595)	(0.614)
log(FAO-GAEZ-Predicted Output)		0.239***				0.273***		
		(0.0704)				(0.0770)		
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	6,844	2,334	6,920	6,069	6,631	2,334	6,696	5,903
R-squared	0.680	0.694			0.679	0.689		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP mismatch with the US and columns 5-8 use CPP mismatch with the estimated set of technological leader countries. 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 A9: CPP Mismach and Output: Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	Panel A: CPP Distance to the US							
CPP Distance (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
	Panel B: CPP Distance to Estimated Frontier Set							
CPP Distance (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
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 dstance to the US and Panel B uses CPP dstance to the estimated set of technological leader countries. 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 A10: 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 US				CPP Mismatch with the Estimated Frontier			
CPP Mismatch (0-1)	-8.925***	-10.20***	-8.695***	-9.355***	-11.89***	-10.10***	-11.85***	-10.37***
	(2.386)	(3.327)	(1.752)	(2.096)	(1.937)	(2.475)	(1.538)	(2.247)
log(FAO-GAEZ-Predicted Output)		0.654***				0.659***		
		(0.138)				(0.133)		
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	1,436	696	1,437	1,093	1,370	696	1,371	1,036
R-squared	0.641	0.680			0.658	0.683		

Notes: The unit of observation is a state-country pair. Columns 1-4 use CPP mismatch with the US and columns 5-8 use CPP mismatch with the estimated set of technological leader countries. 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 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 state and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A11: 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 A12: 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 A13: 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 regresson 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 A14: CPP Mismatch Without Invasive Species: Baseline Estimates

	(1)	(2)	(3)	(4)	(5)
	Technology Trasnfer			Output	Technology Adoption
Dependent Variable:	asinh Biotech Transfer	Any Biotech Transfer	log Biotech Transfer	log Output	Improved Seed (=1)
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				-6.335***	-0.248***
				(0.948)	(0.0743)
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	6,858	115,397
R-squared	0.4397	0.3831	0.7965	0.584	0.213

Notes: The unit of observation is a crop-origin-destination in columns 1-3, a crop-country pair in column 4, and a farm-crop pair in column 5. Standard errors are double-clustered by origin and destination in columns 1-3, double clustered by crop and country in column 4, and clustered by crop-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.

Table A15: Causal Effects of Inappropriateness

		Scenario	
Statistic	Unit	Flexible Prices	Fixed Prices
Reduction in Productivity	Percent	42.2	56.5
		(4.0)	(4.7)
Increase in IQR (75-25)	Percent	15.1	19.7
		(0.4)	(0.7)

Notes: Calculations compare the observed equilibrium with inappropriate technology to the counterfactual equilibrium without inappropriate technology, as described in the main text. Standard errors, in parentheses, are calculated via the Delta Method, using the numerical gradient of statistics to the estimated parameter β. Productivity losses are area-weighted means across countries.

Supplementary Materials
for "Inappropriate Technology: Evidence from Global Agriculture"
by Moscona and Sastry
(Not for Publication)

D. Additional Model Derivations, Proofs, and Extensions

D.1 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

$$u((Y_k)_{k=1}^K) + m \tag{D.1}$$

for some concave u.[40] 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

$$\begin{aligned} \max_{(B_{t,k,\ell',\ell})_{k,\ell',\ell,t\in\mathcal{T}_{k,\ell}},(X_{k,\ell',\ell})_{k,\ell',\ell}} & \left\{ u((Y_k)_{k=1}^K) - \sum_{k=1}^{K}\sum_{\ell=1}^{L}\sum_{t\in\mathcal{T}_{k,\ell}} e^{-\tau(B_{t,k,\ell',\ell'})}\frac{(B_{0,\ell'}B_{t,k,\ell',\ell})^{1+\phi}}{T(1+\phi)} \right. \\ & \left. - \sum_{k=1}^{K}\sum_{\ell=1}^{L}\sum_{\ell'=1}^{L}(1-\gamma)^2 X_{k,\ell',\ell} \right\} \\ \text{s.t .} \ & F_k((B_{t,k,\ell',\ell})_{k,\ell,t\in\mathcal{T}_{k,\ell}}, (Y_k)_{k=1}^K) \leq 0, \ \forall k \end{aligned} \tag{D.2}$$

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

[40]See that, in equilibrium, this household's first order condition for good k is $\partial u((Y_k)_{k=1}^K) \big/ \partial Y_k = p_k$, which pins down the demand system.

each farmer i to crop k.

There are three forces in the model that drive differences between competitive equilibria and social planning. One, which will be our focus in this Appendix, is that the planner internalizes the knowledge spillover. A second, which is standard in models of endogenous (and directed) innovation, is that the planner maximizes total surplus when choosing the quantities $X_{k,\ell',\ell}$ of the technological input (i.e., if the planner were implementing an allocation via prices, they would not charge a mark-up over marginal cost). A third, which is specific to our set-up, is that the planner internalizes the effect of research (and technological good production) on aggregate revenue productivity in each country.

Let λ_k denote the Lagrange multiplier on each dimension of F. Under the assumption that the program in Equation D.2 is concave, the following first-order condition for the choice of $B_{t,k,\ell',\ell}$ is necessary for optimality:

$$\begin{aligned} B_{0,\ell'}^{1+\phi} B_{t,k,\ell',\ell}^{\phi} \exp(-\tau(B_{t,k,\ell',\ell'})) = \lambda_k & \frac{\partial F_k((B_{t,k,\ell',\ell})_{k,\ell,t\in\mathcal{T}_{k,\ell}}, (Y_k)_{k=1}^{K})}{\partial B_{t,k,\ell',\ell}} \\ & + \mathbb{I}[\ell' = \ell]\tau'(B_{t,k,\ell',\ell}) \sum_{\ell''=1}^{L} e^{-\tau(B_{t,k,\ell',\ell})} \frac{(B_{0,\ell'} B_{t,k,\ell',\ell''})^{1+\phi}}{T(1+\phi)} \end{aligned} \tag{D.3}$$

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.

D.2 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 Sections 2.1.1 and

2.1.2. 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

$$\rho_{\ell,\ell'} \begin{cases} 0 & \text{if } \ell = \ell' = 1 \\ \infty & \text{otherwise} \end{cases} \tag{D.4}$$

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 (significant) 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

$$\log \theta_{k,1,\ell} = \alpha \log A_k + \frac{1-\alpha}{T} \sum_{t \in \mathcal{T}_{k,\ell}} \max \left\{ \log B_{t,k}, \log \underline{B}_\ell \right\} \tag{D.5}$$

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 D.5 as

$$\log \theta_{k,1,\ell} = \alpha \log A_k + (1-\alpha)\left((1-\delta_{k,1,\ell}) \log B_k + \delta_{k,1,\ell} \log \underline{B}\right) \tag{D.6}$$

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:

$$\log \theta_{k,\ell',\ell} = \beta_{k,\ell'} \cdot \delta_{k,\ell',\ell} + \chi_{k,\ell} + \chi_{k,\ell'} + \chi_{\ell,\ell'} \tag{D.7}$$

In this case, the fixed effects are given by

$$\begin{aligned} \chi_{k,\ell} &= 0 \\ \chi_{k,\ell'} &= \mathbb{I}[\ell' = 1]\left(\alpha \log A_k + (1-\alpha) \log B_k\right) \\ \chi_{\ell',\ell} &= 0 \end{aligned} \tag{D.8}$$

and the coefficient of interest is

$$\beta_{k,\ell'} = -\mathbb{I}[\ell' = 1](1-\alpha)(B_k - \underline{B}_\ell) \tag{D.9}$$

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 2.2.1).

E. Pathogen 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 like it in the world.

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 it, 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).

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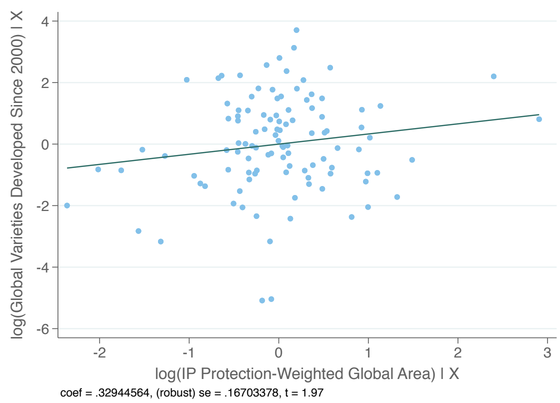
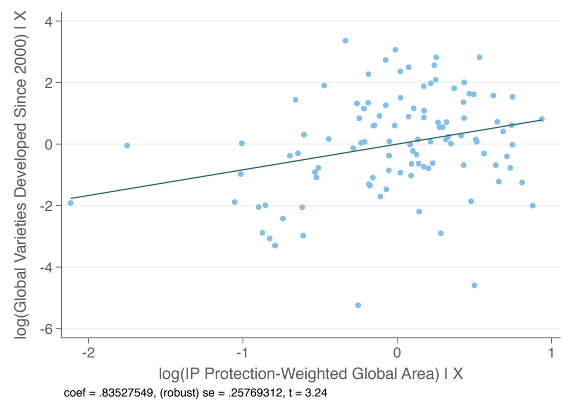
F. Results Corresponding to Analysis in the Online Appendix

Figure B1: Bias in Global BioTech Development

(a) IP-Weighted Area and BioTech Development



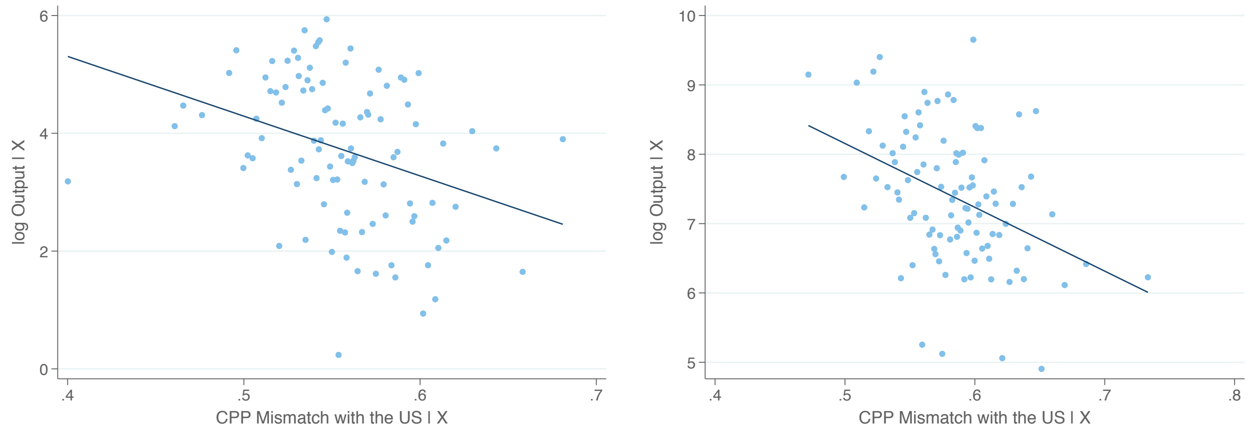
(b) GDP-Weighted Area and BioTech Development



Notes: Partial correlation plots ($N = 107$) of our estimates of δ_2 and δ_3 from Equation (B.3). Both are estimated from the same regression, which also includes a control for log of global planted area.

Figure B2: CPP Mismatch and Agricultural Output: Brazil and India Separately

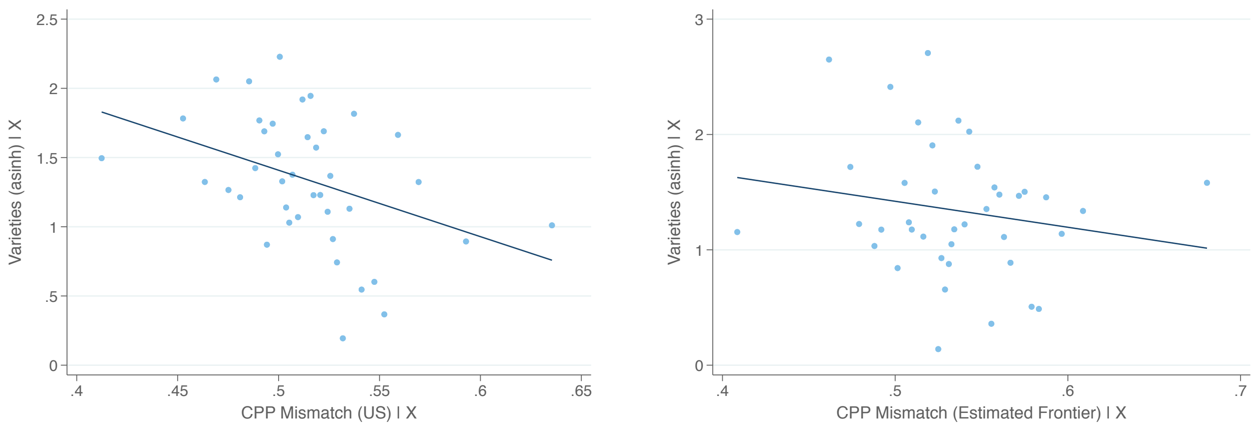
(a) India ($N = 384$) **(b)** Brazil ($N = 1,052$)



Notes: This figure displays binned partial correlation plots, after absorbing crop and state fixed effects, of our estimates of Equation (5.3), separately for India (B2a), where we estimate $\beta = -9.20$ (2.70), and Brazil (B2b), where we estimate $\beta = -10.15$ (5.17).

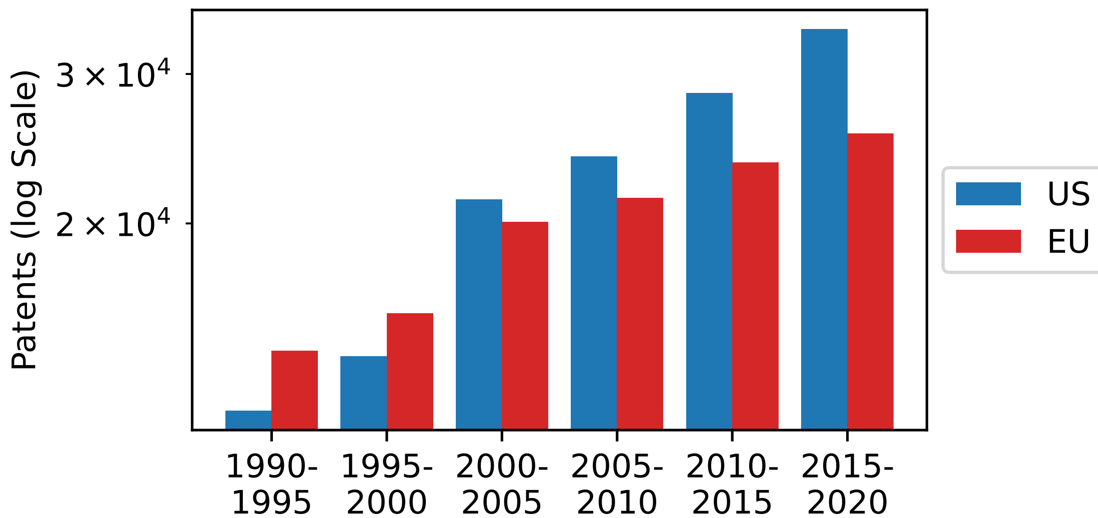
Figure B3: Pathogen Distance and Biotechnology Transfer to sub-Saharan Africa

(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 (B.6), 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 B4: Growth in Agricultural Patented 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.

Table B1: 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 B2: 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 B3: 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: tempearture, 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 B4: 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 B5: Growth of US Biotechnology and 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.