Inappropriate Technology: Evidence from Global Agriculture*

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Abstract

An influential explanation for the persistence of global productivity differences is that frontier technologies are adapted to the conditions of the high-income, research-intensive countries that develop them and significantly less productive if used elsewhere. This paper studies how the environmental specificity of agricultural biotechnology affects its global diffusion and productivity consequences using differences in the presence of unique crop pests and pathogens (CPPs) as an instrument for the potential appropriateness of crop-specific biotechnology developed in one country and applied in another. We find that inappropriateness predicted by CPP mismatch reduces cross-country transfer of novel plant varieties and that the predicted inappropriateness of frontier technology reduces crop-specific output. Our estimates imply that the inappropriateness of the contemporary frontier reduces global agricultural productivity by 50% and increases productivity disparities by 15% relative to a world in which technology were equally productive in all environments. We use our framework to inform debate about the heterogeneous impacts of the Green Revolution, technology adoption among smallholder African farmers, and the possible productivity effects of predicted changes in the geography of innovation.

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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 internationally transmittable and broadly applicable, and concludes that technology diffusion from the frontier can induce productivity convergence in the long run.[1] A second, contrasting school of thought emphasizes that much technological advancement is attuned to specific methods or factors of production (Atkinson and Stiglitz, 1969). Variations of the *inappropriate technology hypothesis* state that frontier innovators' focus on developing technologies that match local characteristics severely inhibits these technologies' usefulness in, and diffusion to, other contexts (Stewart, 1978; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001). In this framework, disparities in research intensity cause productivity to persistently differ across places and cluster in those "similar" to research leaders. The quantitative relevance and global incidence of these predictions, however, remain largely unknown.

This paper empirically investigates the inappropriate technology hypothesis in a context in which all of its underlying forces loom especially large, global agriculture and plant biotechnology. Agriculture features immense cross-country productivity differences (Caselli, 2005), and global R&D is dominated by a small set of biotechnology firms in rich countries (Fuglie, 2016).[2] Despite historical recognition that this inequity may underlie productivity differences, most notably embodied by the Green Revolution of the mid 20th century, the contemporary research gap is not filled by public-sector research, just 3% of which takes place in low-income countries (Beintema et al., 2012), or philanthropically supported research, which also concentrates in wealthy countries.[3]

The core of our strategy for testing and quantifying the inappropriate technology hypothesis is a new measure of potential biotechnological inappropriateness based on the global distribution and crop-specificity of crop pests and pathogens (henceforth, CPPs). CPPs are extensively documented as pre-eminent threats to agricultural productivity and targets for biotechnological innovation. We exploit the fact that a given crop-country's CPP environment is a predetermined shifter for the potential effectiveness of a foreign technology originally developed for a different CPP environment. In our empirical analysis, we study the relationship between this shifter of potential appropriateness with innovation, technology diffusion, and production. We use our estimates to quantify the contribution

[1] Eaton and Kortum (1996) and Barro and Sala-i Martin (1997) formalize how free diffusion of ideas can sustain international growth-rate convergence in Neoclassical endogenous growth models. Parente and Prescott (1994, 2002) suggest that barriers to technology adoption explain an observed lack of income and growth convergence.

[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 breeding or research program (Access to Seeds Foundation, 2019).

[3] Vidal (2014), in an analysis of all grants from the Gates Foundation, find that 4% of funding for non-governmental organizations is invested in Africa, while 75% is invested in US-based organizations.

of observed patterns of research intensity and ecological mismatch toward the global distribution of agricultural productivity. We then study in the calibrated model how plausible counterfactual changes to global research and ecology would affect productivity via the inappropriate technology mechanism. More conceptually, our study provides new evidence on the environment's impact on comparative development via the endogeneity of production technologies. Our analysis implies that "better" or "worse" geographic conditions are not fixed, but instead determined as evolving equilibrium outcomes of endogenous technology development and diffusion.

Toward these goals, we first present a model of production and endogenous innovation in the global agricultural system. Farmers freely choose which crops to grow and what international technologies to use. Profit-maximizing innovators in each country invest research effort into improving both context-neutral attributes of technology and context-specific adaptation to country- and crop-specific environmental features, like the pest and pathogen composition. Local economies of scale, modeled via knowledge spillovers, guide innovators toward developing technology adapted to local environmental conditions 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 estimable regression equations and show how to map reduced-form estimates of these equations to causal effects.

In order to directly measure the potential inappropriateness of context-specific technology across locations, we exploit the differential prevalence of crop pests and pathogens (CPPs) around the world.[4] CPPs are a dominant source of production losses, estimated to reduce annual global output by 50-80% (Oerke and Dehne, 2004). CPP resistance, and tolerance to chemicals that kill harmful CPPs, has been a key focus of traditional plant breeding (Collinge, 2016) and is central to modern transgenic crop development (Dong and Ronald, 2019). The combination of technology's CPP-specificity with large differences in CPP environments around the world can, anecdotally, limit the productivity benefit from adopting foreign, frontier technology. As one example, the Maize Stalk Borer that decimates maize in Kenya is not present in the US, while the Western Corn Rootworm, nicknamed the "Billion-Dollar Bug" for its impact on US 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 Corn Rootworm and Stalk Borer, 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

[4]Of course, the CPP environment is not the *only* characteristic that determines the direction of innovation and appropriateness of technology. In Appendix C.2 we explore the role of non-CPP differences in agro-climatic conditions.

(CABI) Crop Protection Compendium (CPC), the "world's most comprehensive site for information on crop pests." These distribution and host plant data are based on comprehensive expert review of published literature in plant pathology, ecological science, and agronomy (Pasiecznik et al., 2005).[5] The CABI data allow us to enumerate all shared and unique CPP threats affecting any crop and country pair in the world (e.g., maize in the United States and Kenya).

We first verify the premise of the inappropriate technology hypothesis that global research is directed toward combatting CPP threats present in rich countries. Using the CABI data in combination with comprehensive data on global patents that mention specific CPPs, we document that research is highly skewed toward CPPs that are endemic to rich, research-intensive countries. Consistent with the model's premise of home bias in CPP research, countries disproportionately patent technologies referencing locally present CPPs and this force generates the aggregate technological bias toward threats in the high-income countries where innovation takes place.

We then develop a "CPP Distance" 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 treat this measure as our main measure of "potential inappropriateness" of a crop-specific technology adapted for one CPP environment and applied in another. From an empirical design perspective, 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 conduct all subsequent analysis holding fixed differences, ecological or otherwise, purely across crops and/or country-pairs.

Our first main goal is to document how inappropriateness shapes global technology diffusion. We compile 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 varieties from their first introduction to all other countries where they were ever transferred. We find that CPP distance 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 and 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 subsetting to origins with more active biotechnology sectors. This result is consistent with the knowledge spillovers mechanism in the model, and it reveals the especially large technological cost of being environmentally dissimilar from frontier innovators.

Having established that CPP differences inhibit technology diffusion, our second main goal is to investigate implications for global production and specialization. The model predicts that countries should specialize in crops for which ecological conditions most resemble those in frontier innovating nations due to the availability of more appropriate international technology. We measure "CPP

[5]These data are commonly used in population ecology and crop science. See, for example, studies by Bebber et al. (2013), Bebber et al. (2014), Paini et al. (2016), and Savary et al. (2019).

distance to 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' anaysis (e.g. Fuglie, 2016), or (ii) estimating countries that produce and transfer the most varieties for each crop in the PLUTO 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 local suitability and the direct effects of local ecology.[6] These effects are large relative to observed variation in agricultural specialization—a one-standard deviation increase in CPP dissimilarity, across all studied countries and crops, reduces production of a crop by 0.51 standard deviations. We find very similar effects across regions within countries, using state-level production and CPP distribution data from India and Brazil.

Our results so far have investigated the inappropriate technology hypothesis in a modern cross-section of all countries and crops. We next directly investigate the relationship between the appropriateness of technology and realized technology adoption, using two specific case studies in which disparities in technology adoption are the subject of intense debate. We first analyze how inappropriateness shaped the consequences of the Green Revolution of the 1960s and 1970s, perhaps the most concerted effort to shift agricultural innovative focus in history, during which philanthropic organizations funded the development of breeding programs in tropical environments. We find that adoption of these new varieties and expansions of production from 1960-1980 were severely inhibited in country-crop pairs with CPP environments dissimilar to the locations of the international agricultural research centers that led research for specific crops. This supports scholars' arguments that even innovation tailored to more tropical ecosystems was not one-size-fits-all (Pingali, 2012), and directly illustrates how "advantageous" ecology changes over time as international research evolves.

Next, we study whether inappropriateness contributes to the limited use of improved agricultural inputs by smallholder farmers in Africa. Using data from the latest geo-coded round of each World Bank Integrated Survey of Agriculture, we find that farmer-crop pairs with greater CPP dissimilarity to frontier countries are less likely to use improved seed varieties.[7] This suggests that features of frontier technology itself—its poor adaptation to the African environment—may explain a significant portion of farmers' low technological uptake and, by reducing potential market size, even further dissuade the development of advanced agricultural technology in the region.

Having documented each component of the inappropriate technology hypothesis, we return to our model to draw out the aggregate productivity implications after taking into account production reallocation and terms of trade effects. Our calibration combines our reduced-form estimates of

[6]These strategies include: (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 machine learning approach that controls flexibly for a large set of ecological features interacted with crop fixed effects, as well as CPP fixed effects accounting for the direct effect of each CPP. Our findings are consistent with historical evidence suggesting that there was nothing "special" about the agro-climatic characteristics of the US and other frontier countries; in fact, US agricultural history is characterized by continued technological development to overcome persistent ecological challenges (Kloppenburg, 2005; Olmstead and Rhode, 2008).

[7]The Integrated Survey of Africa covers eight countries, including Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda.

the effect of ecological dissimilarity on production and specialization with external estimates of the elasticity of supply to productivity changes. We first study a counterfactual scenario of "removing inappropriateness" by making all frontier technology maximally effective in all locations. According to this exercise, inappropriateness reduces agricultural productivity by 40-50% on average. Losses are concentrated in Asia and Africa, underscoring the relevance of historical and current efforts to encourage biotechnological development in these neglected agricultural ecosystems. These effects explain 10-15% of cross-country differences in (log) productivity, driven by the fact that the countries that are most lacking in appropriate biotechnology are also those that are least productive today.[8]

We next use our model explore how changes in the geography of innovation and ecology would affect patterns of productivity growth in three counterfactuals that more closely resemble real-world scenarios than removing the effect of inappropriateness entirely. In the first, we map out global-output-maximizing locations for "Second Green Revolutions" that would transplant the Frontier for specific crops. Our results convey potentially large output gains from focusing research in India, sub-Saharan Africa, and China. In the second, we study a "BRIC realignment" counterfactual, which replaces the observed biotechnological frontier with Brazil, Russia, India, and China, countries that contribute a rapidly growing share of global R&D. While a far cry from an explicitly targeted "Second Green Revolution," this scenario is on net favorable for the world's least productive agricultural nations while harmful toward parts of Europe and North America. In the third, we study a potentially large shift in the habitable range of CPPs due to climate change (Bebber et al., 2013), which changes the "ecological distance" between countries even while holding the identity of the frontier fixed. Our admittedly speculative finding is that climate change could coordinate international research on a more common set of productivity threats, and therefore the inappropriate technology mechanism should ameliorate some of the direct productivity losses.

This paper builds on a largely theoretical body of work on the role of "appropriate technology" in shaping productivity differences (Atkinson and Stiglitz, 1969; Stewart, 1978). Early studies investigated the specificity of technical advances and barriers to their adoption within countries (Griliches, 1957; David, 1966; Salter, 1969). Stewart (1978) discusses how the inappropriateness of rich-country technology for application in low-income countries could present a major barrier to economic development. More recent work 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). Our focus on immutable ecological differences is both conceptually and practically different, as it does not interact with economic incentives for factor accumulation and cannot be affected by policy.

A large literature has studied the *direct* effects of adverse environmental conditions on economic development (see, for instance, Kamarck, 1976; Sachs and Warner, 1997; Gallup et al., 1999). We focus instead on how ecological differences affect the development and diffusion of technology. This

[8]Our preferred measure of "differences" for this calculation is the inter-quartile range of the cross-country distribution of land productivity; similar results are obtained using different measures.

confluence of ecology and technology diffusion is one mechanism in the theory of Diamond (1997), who discusses the easier diffusion of agricultural technology across "horizontal" landmasses. Our paper thus builds on a more recent analysis of geography's role in development, which suggests that geography and ecology affect modern productivity via their interactions with historical events and their role in shaping political institutions and culture (e.g., Sokoloff and Engerman, 2000; Acemoglu et al., 2001; Engerman and Sokoloff, 2002; Nunn and Puga, 2012; Alesina et al., 2013).

By proposing and quantifying a new source of productivity differences in global agriculture, we build on a large body of work investigating the sources of international disparities in agricultural production (e.g. 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 (e.g., Foster and Rosenzweig, 1996, 2004; Evenson and Gollin, 2003b,a; Pingali, 2012).

At the center our hypothesis are the determinants of technology diffusion (Keller, 2004; Kerr, 2008; Comin and Mestieri, 2014). Relevant work includes macro-level studies of technology diffusion in the 18th century (Comin and Hobijn, 2004, 2010; Comin and Mestieri, 2018) and micro-level studies of technology upgrading in modern times (Bandiera and Rasul, 2006; Conley and Udry, 2010). While most work in this area focuses on the characteristics of producers, our study documents how the focus of innovation shapes patterns of technology use and productivity. Related to our hypothesis, Suri (2011) argues that differences in hybrid maize adoption in Kenya reflect differences in returns to adoption—a feature of the technology itself—and not adoption frictions.

Finally, there is a broad parallel between our analysis of ecological difference and its effects on agricultural biotechnology development and studies of globally heterogeneous human disease burdens. "Neglected Tropical Diseases," which receive little attention from medical researchers in advanced economies (Kremer, 2002; Kremer and Glennerster, 2004) and inflict heavy health damages in many tropical and low-income countries (Hotez et al., 2007, 2009).

This paper is organized as follows. Section 2 describes a theoretical model that structures our empirical analysis and quantification. Section 3 provides background information on the ecological specificity of biotechnology and describes our measure of inappropriateness. Section 4 reports our results on international technology transfer, Section 5 reports our results on production, and Section 6 presents our additional results on technology adoption. Section 7 quantifies the total effect of inappropriateness and explores counterfactual scenarios. Section 8 concludes.

2. Model

We first present a model of agricultural innovation, technology diffusion, and production. We use the model to introduce the key economic mechanisms of the inappropriate technology hypothesis, adapted to our setting, and generate estimable equations for the relationship of ecological differences with technology diffusion and production.

2.1 Set-up

2.1.1 Locations, Production, and Planting

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 (e.g., crop varieties) indexed by its country of origin. Potential physical output of a farm producing crop k, with technology ℓ', in country ℓ, on farm i is denoted by the random variable $\psi_i(k, \ell')$. Potential productivity is the product of three terms:

$$\psi_i(k, \ell') = \omega(k, \ell) \cdot \theta(k, \ell' \to \ell) \cdot \varepsilon_i(k, \ell') \qquad \forall i \in [\ell - 1, \ell) \tag{2.1}$$

The first term, $\omega(k, \ell) \in \mathbb{R}_+$, captures average innate productivity for crop k in country ℓ. The second term, $\theta(k, \ell' \to \ell) \in \mathbb{R}_+$, captures the productivity of technology from ℓ' used in ℓ. The third term $\varepsilon_i(k, \ell' \to \ell)$, is an idiosyncratic perturbation with a Fréchet distribution with mean one and shape parameter $\eta > 0$.[9] The random component captures un-modeled plot-level heterogeneity and disciplines the elasticity of average farmer choices to changes in innate or technological productivity.[10]

Each location-by-crop pair is associated with a set $\mathcal{T}(k, \ell)$ of local ecological characteristics, which are normalized to have measure one and may possibly overlap between countries for a fixed crop. The identity of these characteristics may be a determinant of location-specific productivity $\omega(k, \ell)$. Henceforth, to be consistent our main empirical analysis, we will think of this set enumerating all locally present crop pests and pathogens (CPPs), although our model is sufficiently abstract not to rely on this interpretation.

Finally, farmers face an international price $p(k)$ for each crop k and pay input costs equal to a fraction $\overline{\rho} < 1$ of revenue.[11] Each farmer in country ℓ observes prices and potential productivities, and chooses a crop-technology combination to maximize revenue. This discrete choice structure for production and specialization is similar to that adopted by Eaton and Kortum (2002), Costinot et al. (2016), and Sotelo (2020), and it will enable tractable analysis.

2.1.2 Endogenous Technology and Inappropriateness

In each country ℓ', there is a continuum of symmetric innovators indexed by $j \in [\ell' - 1, \ell')$, who develop technology for each of the crops k and own an equal fraction of each global (k, ℓ') technology market. Each innovator's technology is described by a general characteristic, $A_j(k) \in \mathbb{R}_+$, and a vector of resistances to specific CPPs, $(B_j(t, k, \ell))_{t \in \mathcal{T}(k,\ell)} \in \mathbb{R}_+^{|\mathcal{T}(k,\ell)|}$. These characteristics combine to

[9] The normalization to mean one implies that the scale parameter is $(\Gamma(1 - \frac{1}{\eta}))^{-1} > 0$. This normalization is convenient for subsequent expressions; otherwise the scale factor would scale aggregate productivity.

[10] The specific Fréchet distributional assumption has two roles. First, it allows for simple analytical expressions for farm choices. Second, it determines the relationship between average and marginal products of land conditional on a specific use. Proposition 2 and the subsequent discusison highlight this latter property.

[11] We focus in this section on a world economy with fixed prices. It is straightforward to extend all analysis to a case in which prices are determined along a world demand curve for each crop.

determine the overall productivity of innovator j's technology in the following way:

$$\theta_j(k,\ell) = \exp\left(\alpha \log A_j(k) + (1-\alpha)\int_{\mathcal{T}(k,\ell)} \log B_j(t,k,\ell)\,\mathrm{d}t\right) \qquad \forall j \in [\ell'-1,\ell') \tag{2.2}$$

where $\alpha \in (0,1)$ parameterizes the relative importance of the general characteristic. General characteristics, by definition, boost the productivity of technology in all locations ℓ. Investment in resistance to CPP t boosts productivity in all locations that have that CPP, or $\{\ell : t \in \mathcal{T}(k,\ell)\}$. And the two are complementary to one another: high general productivity increases the marginal value of resistance, and vice-versa.

Our goal with these modeling choices may be best illustrated via an example in our setting, the development of high-yield wheat varieties during the 1960s at the International Maize and Wheat Improvement Center (CIMMYT) in Mexico, spearheaded by famous agronomist Norman Borlaug. An important advancement for overall yield potential ("improvement in A") was incorporating semi-dwarfism into local wheat varieties, a trait that made wheat stalks shorter and less likely to topple over before harvest. Incorporating dwarfism dovetailed with CIMMYT's ongoing efforts to breed resistance ("improvement in B") to fungal wheat rusts, a globally ubiquitous threat to production. CIMMYT wheat varieties contained both semi-dwarfism and rust-resistance traits (Reynolds and Borlaug, 2006). A retrospective field trial of two decades of CIMMYT wheat varieties by Sayre et al. (1998) highlighted how improvement in yield potential was, in terms of practical field performance, dwarfed by improvements in protecting those yields from leaf rust. This is consistent in our model with the assumed $\alpha \in (0,1)$ and complementarity between the two components.

We now return to specifying the decision problem of innovators. Innovators choose the characteristics of technology maximize profits, which equal a fraction $\rho(\ell,\ell') \leq \overline{\rho}$ of their customers' revenue (e.g., net of trade and licensing costs), net of convex, additively separable research costs. We write the costs of CPP-resistance technology as $C(z;t,k,\ell')$, for research level z, CPP t, crop k, and innovating country ℓ'.[12] We assume these costs have a power form, parameterized by coefficient $\phi > 0$ with a *knowledge spillover* from average local research on the pest, $B(t,k,\ell' \to \ell') := \exp\left(\int_{\ell'-1}^{\ell'} \log B_j(t,k,\ell')\,\mathrm{d}j\right)$. The costs can be written, up to a parameter $\tau > 0$ controlling the intensity of spillovers and a constant $B_0 > 0$, as:[13]

$$C(z;t,k,\ell') = \exp\left(-\tau B(t,k,\ell' \to \ell')\right) \cdot \frac{(B_0 z)^{1+\phi}}{1+\phi} \tag{2.3}$$

The knowledge spillover creates a local economy of scale and could embody local sharing of ideas, or more literally the presence of local test fields, availability of local germplasm, and domestic economies of scale that are contributing factors to agricultural technology development.[14] Practically, in the

[12] The costs of general technology need not be specified to derive our main results.

[13] We will further require the technical condition $\phi > \eta - 1$ to ensure that the fixed-point equation determining technology quality has well-behaved, monotone comparative statics for any value of α.

[14] The relationship between local economies of scale and "technology export," which we will formalize soon, resembles

CIMMYT example, wheat varieties exported throughout the developing world were orignally field-tested against the Mexican CPP environment and heavily based on Mexican germplasm. We will discuss additional examples at length in Section 3.1.

Finally, we define aggregate technology as the geometric average of innovator-specific technology, or $\log \theta(k, \ell' \to \ell) := \int_{\ell'-1}^{\ell'} \log \theta_j(k, \ell)\, \mathrm{d}j$. We focus on symmetric equilibria of the previous model in which all (crop-by-country indexed) innovators and (country indexed) farmers make uniform choices.

2.2 Main Predictions

In Appendix B, we include detailed derivations of necessary conditions for any symmetric equilibrium of the model. Here, we highlight the main predictions which motivate our empirical analysis.

2.2.1 Technology Diffusion

Let $\delta(k, \ell', \ell)$ be the measure of k-CPPs that are not shared between locations ℓ and ℓ'. We first formalize how technology depends negatively on the ecological dissimilarity between locations, as summarized by $\delta(k, \ell', \ell)$:

Proposition 1. *Technology diffusion from country ℓ' to ℓ for crop k can be expressed as*

$$\log \theta(k, \ell' \to \ell) = \beta(k, \ell') \cdot \delta(k, \ell', \ell) + \chi(k, \ell) + \chi(k, \ell') + \chi(\ell, \ell') \tag{2.4}$$

where the $\chi(\cdot)$ are additive effects varying at the indicated level and

$$\beta(k, \ell') = -\frac{(1-\alpha)\tau B(k, \ell')}{1 + \phi - (1-\alpha)\eta} \leq 0 \tag{2.5}$$

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

Technology developed in country ℓ' for ℓ is biased toward ℓ'-present threats due to the knowledge spillover. If the receiving location ℓ shares the same threats as ℓ', it will therefore receive higher-quality technology, all else equal. The null hypothesis of a zero effect of CPP differences is associated in the model with purely general-purpose technology ($\alpha = 1$), a zero knowledge spillover ($\tau = 0$), infinitely inelastic research supply ($\phi \to \infty$), or zero research on pests and pathogens in the technology-sending country ($B(k, \ell') = 0$).[15] Away from zero, the effect of inappropriateness on technology diffusion, or $|\beta(k, \ell)|$, is predicted to smoothly increase in the extent of research in the sending country. This formalizes the intuition that inappropriateness is particularly costly relative to technological "leaders" with high levels of research. We will estimate Equation 2.4 in Section 4 treating counts of uniquely identified biotechnologies transferred across borders as a proxy for $\theta(k, \ell' \to \ell)$.

in this way the original argument of Krugman (1980) for the *home market effect* for standard goods.

[15] Our assumptions on parameters ensure that $2(1+\phi) - \eta \geq 0$. Practically, this ensures that there is a fixed point between technological improvement and expansion of the market. For completeness, observe also that $|\beta(k, \ell)|$ decreases in ϕ, the convexity of research costs, and increases in η, the elasticity of supply or controller of the aforementioned market expansion.

In Appendix B.4, we state and prove an additional result showing how technology adoption, defined by the fraction of crop k farmers in ℓ using ℓ' technology, can also be written as a decreasing function of CPP dissimiarity $\delta(k, \ell', \ell)$ holding fixed factors at the same level as those in Equation 2.4. In the fixed-point of technology demand and endogenous technology supply, a higher elasticity of technology choice to ecological difference increases the direct market-size effect of the former, and further dissuades technology development. In Proposition 1, this "demand channel" manifests in the fact that $|\beta(k, \ell)|$ increases in η. In Section 6, we will estimate the relationship between inappropriateness of foreign technology and technology adoption and interpret it as a direct test of the demand channel which contributes to depressed technology transfer.

2.2.2 Planting, Production, and Productivity

We next translate the consequences of inappropriate technology for production. A key issue which 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 *un*suitable land. Due to this selection effect, the appropriateness of technology has ambiguous effects on measured productivity, or value-added per unit of land, but unambiguous effects on the total quantity of production or specialization across crops.

We now derive the exact predictions obtained for production, planted area, and revenue yield in our model. Toward this end, we define the *crop technology index* $\Theta(k, \ell)$ and *revenue productivity index* $\Xi(\ell)$ as a function of local technology and productivity shifters:

$$\Theta(k, \ell) = \left(\sum_{\ell'=1}^{L} \theta(k, \ell' \to \ell)^{\eta} \right)^{\frac{1}{\eta}} \qquad \Xi(\ell) = \left(\sum_{\ell'=1}^{L} \Theta(k, \ell)^{\eta} \omega(k, \ell)^{\eta} p(k)^{\eta} \right)^{\frac{1}{\eta}} \tag{2.6}$$

Proposition 2. *The following are true:*

1. *Production of crop k in country ℓ, $Y(k, \ell) > 0$, is given by*

$$\log Y(k, \ell) = \eta \log \Theta(k, \ell) + \eta \log \omega(k, \ell) + (\eta - 1) \log p(k) + (1 - \eta) \log \Xi(\ell) \tag{2.7}$$

2. *Planted area of crop k in country ℓ, $x(k, \ell) \in (0, 1)$, is given by*

$$\log x(k, \ell) = \eta \log \Theta(k, \ell) + \eta \log \omega(k, \ell) + \eta \log p(k) - \eta \log \Xi(\ell) \tag{2.8}$$

3. *The physical yield of crop k in country ℓ, $z(k, \ell) > 0$, is given by*

$$\log z(k, \ell) = \log \Xi(\ell) - p(k) \tag{2.9}$$

Planted area and production are monotone in the quality of technology from each source country, and by implication in any shock that increases these productivities. Crop and country effects absorb any fixed characteristics of crops or countries, including crop prices or country-level average productivity. Log yields, conditional on the same absorbed effects, are predicted to have no relationship with measured technological inappropriateness, due to the Fréchet model's prediction that selection effects directly net out with direct productivity effects.

In our empirical analysis of Section 5, we will estimate Equations 2.7 and 2.8, with production and area as dependent variables, using CPP dissimilarity from an empirically identified "technological frontier" to span $\log \Theta(k, \ell)$. This will allow us to directly measure the effect of inappropriateness on production choice and specialization.

2.3 A Simple Example: Disparities in a Unipolar World

We finally use an example case of the previous model to analytically illustrate the economic consequences of inappropriate technology and set up our counterfactual analysis in Section 7. Consider a world in which only one country, indexed as the Frontier F, supplies biotechnology. This country inelastically supplies for each crop k general research $\overline{A}$, own-CPP research $\overline{B}$, and foreign-CPP research $\overline{B}\exp\left(-\tau\overline{B}\right)$. We consider a limit of $\tau \to \infty$ and $\phi \to \infty$ such that $\beta(k, F) \to -\overline{B}$. These assumptions stylize a world in which technology flows outward from the frontier, but environmental differences embodied in the parameters $(\delta(k, \ell, F))_{k,\ell}$ determine what countries and industries are best positioned to benefit from this technology.

In each country ℓ, the planted fraction of a given crop k is given by

$$\pi(k, \ell) = \frac{\left(p(k)\omega(k, \ell)\exp\left(-\overline{B}\delta(k, \ell, F)\right)\right)^{\eta}}{\sum_{k'=1}^{K}\left(p(k')\omega(k', \ell)\exp\left(-\overline{B}\delta(k', \ell, F)\right)\right)^{\eta}} \tag{2.10}$$

In any country ℓ, production is biased toward crops with environmental conditions that resemble the Frontier's; and, fixing a crop k, production is concentrated in locations with environmental conditions that resemble the Frontier's. The extent of this bias depends on both the direct productivity consequence of inappropriateness, $\overline{B}$, and the elasticity of supply to productivity, η.

Overall productivity in country ℓ is

$$\Xi(\ell) = \overline{A}^{\alpha}\overline{B}^{1-\alpha}\left(\sum_{k=1}^{K}\left(p(k)\omega(k, \ell)\exp\left(-\overline{B}\delta(k, \ell, F)\right)\right)^{\eta}\right)^{\frac{1}{\eta}} \tag{2.11}$$

Research in the Frontier, embodied in $\overline{A}^{\alpha}\overline{B}^{1-\alpha}$, uniformly shifts out global productivity, but ecological differences determine its full effects. To see this most clearly, it is useful to write a log-linear

approximation of country ℓ's productivity around $\delta(k, \ell, F) = 0$, for all k, which yields the following:

$$\log \Xi(\ell) - \log \Xi(F) \approx -\overline{B} \sum_{k=1}^{K} \tilde{\pi}(k, \ell)\delta(k, \ell, F) \tag{2.12}$$

where the $\tilde{\pi}(k, \ell)$ are the fraction of land planted of k in ℓ absent inappropriate technology (e.g., with only "natural" productivity). Equation 2.12 defines a "loss due to inappropriateness," relative to a counterfactual that removes the imperfect alignment of productivity threats across countries. This loss is high if the frontier is highly specialized in environmentally-specific technology (high $\overline{B}$), average envrionmental differences are high (high $\delta(k, \ell, F)$), and environmental differences are concentrated in crops in which the country would counterfactually specialize most (high covariance of $\tilde{\pi}(k, \ell)$ and $\delta(k, \ell, F)$).

In Section 7, we will use this subsection's framework, calibrated by our empirical estimates, to quantify productivity losses due to inappropriateness in the observed equilibrium. We will then use the model to study counterfactual scenarios which change the geography of innovation and, by implication, the levels of and disparities in the global productivity distribution.

3. Background and Measurement: Agricultural Pests and Pathogens

To set-up our empirical analysis, we next provide background information about pest targeting in biotechnology. We then provide a detailed description of our main data source and measure of inappropriateness based on the dissimilarity of pest and pathogen environments for growing specific crops across different 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). 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 1950s and 1960s to increase agricultural productivity in other countries via technological diffusion largely failed because of the "general unsuitability of U.S. temperate zone materials and practices 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." 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.[16]

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, 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.[17] 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 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 international appropriateness of GM technologies therefore emerge as a result of focus on "rich-world pests."[18]

[16]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.

[17]δ-endotoxins produced by Bt were originally identified as candidate toxins specifically because of their effectiveness against these particular pests (Bessin, 2019). Monsanto's Bt corn varieties, MON863 and MON810 were developed with δ-endotoxins selected for their effectiveness against maize rootworm, uncommon among Cry proteins (Galitsky et al., 2001).

[18]This pattern in GM development is not restricted to corn. The first varieties of Bt Cotton introduced in the early 1990s

3.2 Plant Pest and Pathogen Data: The Crop Protection Compendium (CPC)

While the aforementioned examples highlight specific instances of pest-specificity, it is unclear whether they are representative of general biases agricultural technology. Our analysis, unlike existing field tests of specific varieties or case studies, 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 aggregate consequences. We now introduce the key data that allow us to directly measure CPP dissimilarities across all global crop-specific ecosystems and work toward that goal.

We source information on the global distribution of crop pests and pathogens from 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 (a non-profit) the UN Food and Agriculture Organization, and the Technical Centre for Agricultural and Rural Cooperation (CTA). The goal of the project is to develop comprehensive and 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 (USDA), and the Consultative Group on International Agricultural Research (CGIAR) (Pasiecznik et al., 2005).[19]

In total, we compile information on 4,951 plant pests and pathogens, including viruses, bacteria, insects, fungi, and weeds. For each species, the CABI-CPC provides several key pieces of information. First, it provides information on the 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.

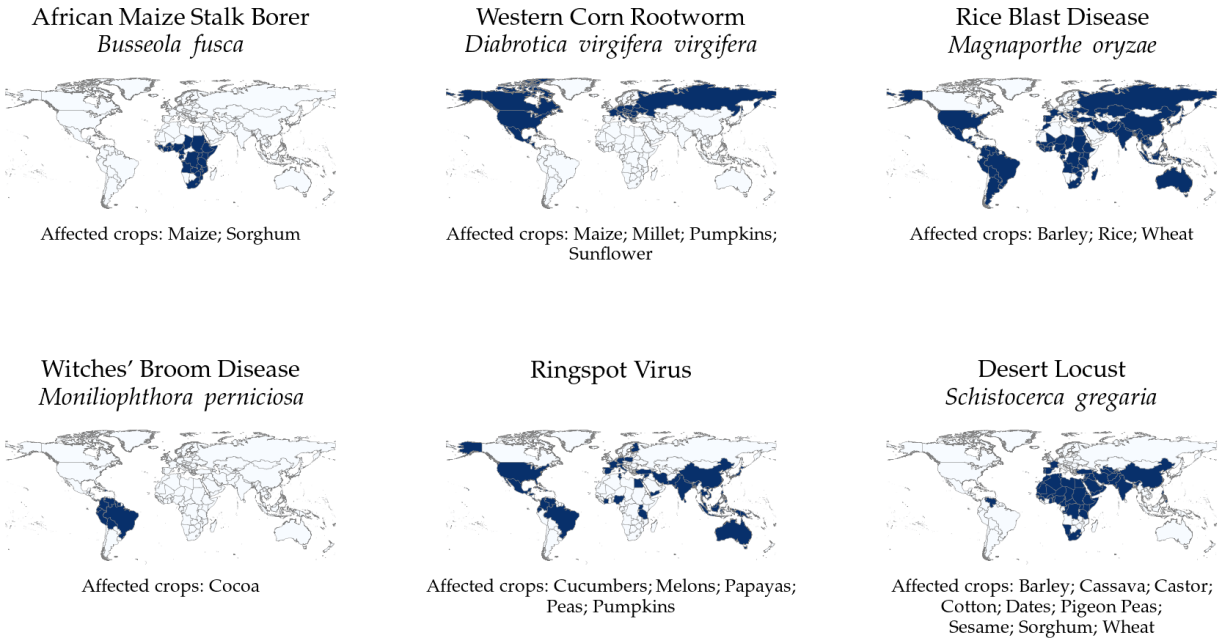
Second, CABI reports all the host species that each pest or pathogen affects. For example, CABI reports that the African Maize Stalk Borer consumes maize and sorghum, while the Western Corn Rootworm consumes maize, millet, pumpkins, and sunflower, but not sorghum (Figure 1, top panel).[20] Our data contain information on 132 host species that are major crops, cross-referenced against the crops used in our subsequent analyses of biotechnology intellectual property and production.

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 due to the lower relevance of the pink bollworm threat in the United States. Tabashnik and Carrière (2019) provide a review of pink bollworm resistance in global cotton populations.

[19] See here: https://www.cabi.org/publishing-products/crop-protection-compendium/

[20] We restrict attention to the host-pest relationships that are verified in the CABI database as opposed to those labeled as "data-mined" from articles and abstracts but not verified. This procedure retains 88% of all possible host-pest matches.

Figure 1: Data on Example CPPs



Notes: Each map is color coded based on the presence of the noted pest in all countries in the world according to the Crop Pest Compendium (CPC) published by the Centre for Agriculture and Bioscience International, our main data source on the distribution of plant pests and pathogens.

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.[21] We also identify the country of origin of each patent using *PatSnap*'s determination of the asignee's location. We document three facts about patenting at the country-by-CPP level, all consistent with the premise of the inappropriate technology hypothesis and the way this premise was encoded in the model.

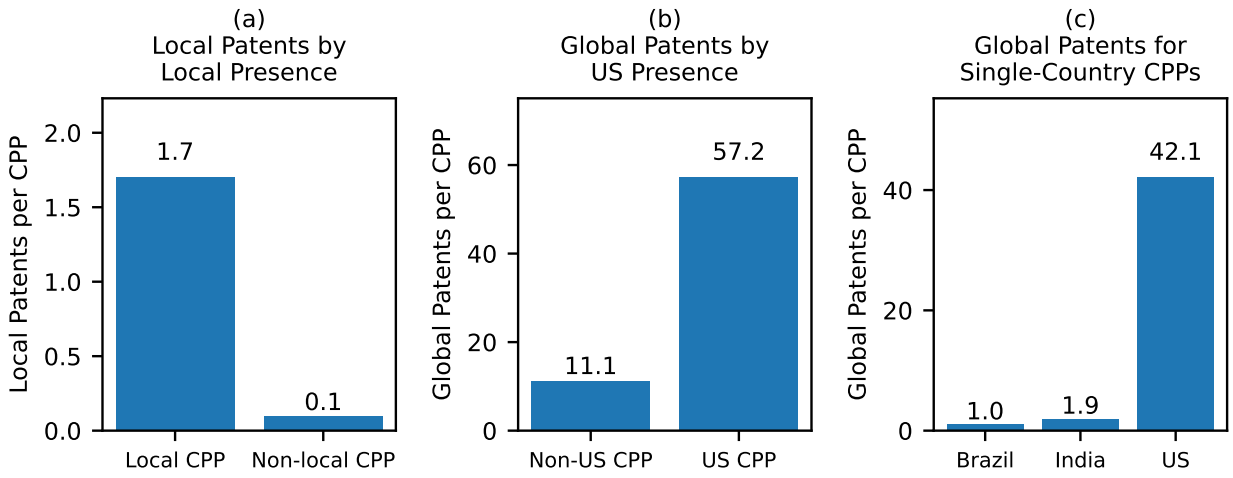
First, a large share of global innovation is focused on crop pests and pathogens (CPPs). Under our classification, 33% of biological and chemical agricultural patents are related at least one CPP.

Second, innovators focus substantially more on locally present CPPs. 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 systematically by estimating the following regression:

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

[21]The full set of biological or chemical agricultural patents are all those that comprise Cooperate Patent Classes (CPC) A01H and A01N. Individual patents can link to multiple CPPs if the patent references multiple species.

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.

where Local CPP(ℓ, t) is an indicator that equals one if CPP t is present in country ℓ, and $y_{\ell,t}$ is the number of patented technologies developed in country ℓ related to CPP threat t, transformed by the inverse hyperbolic sine (asinh). χ_ℓ and χ_t absorb country and CPP fixed effects, and ξ captures the extent to which innovation is disproportionately targeted toward local pathogen threats. Table A2 reports our estimates. We estimate that $\xi > 0$ in Equation 3.1, and that it remains large and significant focusing on either the intensive or extensive margin separately (columns 2-3).

Third, 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 have a more than fivefold higher quantity of patents on average than those not present in the US. Table **??** reports estimates from an augmented version of (3.1) in which Local CPP(ℓ, 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 illustrates an example of one particularly striking cut of the data: the number of patents about CPPs that are present *only* in, or endemic to, the US dwarfs the number for CPPs present only in two of the world's largest, but significantly less research intensive, agricultural economies, Brazil and India.

This analysis, taken together, documents that a large share of global agricultural innovation is focused on CPPs. But much of this research is highly localized, creating an aggregate bias toward research on the "rich world's" productivity threats.

3.4 Measuring Inappropriateness: CPP Distance

The remainder of our empirical analysis, starting from the premise of unequal research intensity, will study the model's predictions for how ecological differences affect technology diffusion and production. To operationalize our empirical tests, we construct an instrument for the potential inappropriateness of technology developed for crop k in country ℓ' for use in country ℓ, due to the differential incidence of CPPs. Using our lists of locally present CPPs affecting crop k in each location ℓ or ℓ', we compute the following measure of "CPP Distance" at the location-pair-by-crop level:[22]

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

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 Distance formulation in (3.2) is one of severals 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'.[23]

CPP Distance 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: for each example in Figure 1, the set of affected crops varies substantially. 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, Appendix Figure A1 shows the histogram of all countries' CPP distance to the US for wheat and sugarcane and identifies the observations for Brazil and India. For wheat, India is very slightly more similar to the US than Brazil is. For sugarcane, Brazil is substantially more similar to the US than India is. Having these two sources of variation allows us to fully control for any differences across countries or crops in our empirical analysis.

Our baseline measure of CPP distance uses all CPPs in the CABI database in order to capture the full extent of CPP differences around the world today. To investigate the potential role of invasive species, which are an important mechanism but also potentially endogenous to human behavior, we can use the CABI Invasive Species Compendium (ISC) to identify high-invasive-potential CPPs

[22] Throughout, we refer to this measure as a "distance" although it does not satisfy a triangle inequality.

[23] We will also, as a robustness check throughout our analysis, supplement our main measure with the simplest and most historical measure of divergence due to Jaccard (1900, 1901) which counts the fraction of non-shared species:

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

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.

and drop them from the calculation of CPP Distance. The ISC data and corresponding analysis are discussed in more detail in Appendix Section C.1.

We also investigate the importance of non-CPP differences in ecology and geography—including temperature, precipitation, soil characteristics—as additional shifters of appropriateness. Appendix Section C.2 discusses our measurement of alternative sources of crop-by-country-pair differences, as well as all empirical results using these alternative measures alongside our baseline CPP distance measure. In summary, we find that differences in other agro-climatic features also inhibit technology transfer and distort specialization; that these effects are independent from the effects of CPP dissimilarity; and that the effects of CPP dissimilarity are larger. These results, along with the anecdotal evidence about plant breeding and technology diffusion from earlier in this section, justify our focus on CPP differences in the primary analysis.

4. Main Results: Technology Diffusion

In this section, we empirically study the relationship between inappropriateness and technology transfer. Our empirical strategy uses variation in inappropriateness and technology transfer at the country-pair-by-crop level, respectively from our CPP Distance measure introduced in the previous section and a new database of international intellectual property protection for plant varieties introduced shortly. This analysis allows us to test and quantify the model's prediction that ecological differences inhibit biotechnology transfer, which underpins the subsequent predictions about production, specialization, and productivity.

4.1 Data: The UPOV Plant Variety Database

We measure the development and international transfer of biotechnology inventions using a novel data set 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.[24] 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.[25] For each certificate, we observe (i) the date of issuance; (ii) the country of issuance; (iii) the plant species; and (iv) 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.[26] This

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

[25]This set notably excludes several large agricultural producers in South Asia, North Africa, and Sub-Saharan Africa, on account of these countries' imperfect recognition of plant variety intellectual property. We return to this topic at various points in the analysis, including with an alternate measure of variety presence in Sub-Saharan Africa (see Section C.4).

[26]This stipulation is described in Article 20.5 ("Same denomination in all Contracting Parties") of the most recent (1991) revision of the UPOV Convention (Union for the Protection of New Varieties of Plants, 1991). Further clarification is

Figure 3: Example Rows from UPOV Data Set

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

allows us to track the diffusion of individual varieties throughout the world, which we also refer to interchangeably as "technologies" when there is no ambiguity. The certificate data, when cross-linked to a list of major agricultural crops and screened for duplicate entries, consists of 458,034 total variety registrations, spanning 62 countries, 109 crops, and 236,529 unique denominations.

To better illustrate the aforementioned features of the data, and introduce our method for measuring technology transfer, we provide a snapshot of part of the data set in Figure 3. 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). The data reveal that 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.[27]

We generalize the above example into a method for tracking the diffusion of specifically identified pieces of technology, like Sicot 41 cotton, between locations. For every unique denomination in the data, we identify a country of first appearance. We use the country of first appearance as the origin country since this is most likely to be the market for which the variety was first developed.[28] We then count, in any given time period, the number of varieties identified for a crop k, newly registered in country ℓ', and originating from country ℓ. This will be our primary measure of technology transfer or 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 registration events after 2000.[29]

Echoing the previous discussion about the concentration of innovation in richer countries, 67% of all recorded varieties are first reported in one of the United States, Canada, or a European Union

provided in the "Explanatory Notes" on variety denominations (Union for the Protection of New Varieties of Plants, 2015).

[27]Sicot cotton is a product of Australia's Commonwealth Scientific and Industrial Research Organization, an Australian governmental agency, which incorporates genetic modification to achieve "desired fibre quality, disease resistance and yield." See here: https://csiropedia.csiro.au/cotton-breeding-and-new-cotton-varieties/.

[28]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, is 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.

[29]Note that we do not truncate the data to post-2000 when identifying country of origin, so a variety like Sicot 41 in the example (first registered in 1999 in Australia) is still in our final data set as a variety transferred to Argentina in 2001.

member state.[30] Among all varieties, 34% are transferred at least once between countries. This number increases to 49% when subsetting to varieties first reported in the aforementioned set of countries, offering a first indication that varieties from "leader countries" are more often spread worldwide. Figure A3 presents summary statistics on the likelihood of variety transfer in our sample and visualizes the network structure of variety transfers across countries. Appendix C.3 also 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. We show that there is a strong concentration of innovation in crops cultivated in high-income and in countries that enforce IP protection for plant biotechnology, and that this effect is driven by substantial home bias toward locally abundant crops.

4.2 Empirical Model

Our main estimating equation is the following linear regression:

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

where k indexes crops, ℓ indexes technology receiving countries, and ℓ' indexes technology sending countries. The outcome $y_{k,\ell',\ell}$ 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 many 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, common geography, trade linkages, etc.).[31] Standard errors are double-clustered by origin and destination.

The main hypothesis is that $\beta < 0$, which would indicate that the local focus and context specificity of innovation depresses technology diffusion and that, on average, biotechnology flows less when technology is inappropriate. We may find no effect, however, if the context-specific component of technological progress or local research spillovers are relatively small.

While estimates of β from Equation 4.1 capture the average relationship between CPP distance and technology transfer, Proposition 1 of the model highlighted that the effect could be very different across crop-origin pairs; in particular, the marginal effect of ecological dissimilarlity should be larger when the sending country is very active in research for crop k. To empirically investigate this idea, we also estimate versions of the following augmented version of (4.1) that parameterizes heterogeneity

[30] These constitute 26 of the 62 countries in our sample.

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

Table 1: CPP Distance Inhibits International Technology Transfer

Dependent Variable:	(1) Biotech Transfer (asinh)	(2) Any Biotech Transfer (0/1)	(3) log Biotech Transfer
CPP Distance (0-1)	-0.0605**	-0.0270**	-1.072***
	(0.0241)	(0.0109)	(0.361)
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.

in the main effect :

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

where $F_{k,\ell'}$ is an indicator variable that equals one for the countries ℓ' that we identify as the biotechnological leaders for crop k. We have two strategies for defining $F_{k,\ell'}$. The first is to treat the United States as the frontier for all crops, or set $F_{k,\ell'} = \mathbb{I}[\ell' = \text{US}]$. This method is motivated by the United States' pre-eminence in modern agricultural research.[32] The second is to identify a set of crop-specific "leaders" $T_N(k)$ in the PLUTO 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. Our hypothesis is that $\beta_2 < 0$, or that the marginal effect of inappropriateness on technology diffusion is largest for the most research intensive origin countries.

4.3 Results

Estimates of Equation 4.1 are reported in Table 1. On all margins, we find that CPP distance significantly inhibits the international flow of technology. The intensive-margin estimates from column 3 imply that CPP dissimilarity inhibits 30% of international technology transfer for the median crop and country-pair, suggesting that even in the full sample crops and countries CPP distance is a major barrier to international technology diffusion.

[32]The US alone produced 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 Distance to Frontier Countries and Technology Transfer

Frontier defined as:	(1) United States	(2) Top Variety Developer	(3) Top 2 Variety Developers	(4) Top 3 Variety Developers
	Panel A: Dependent Variable is (asinh) Biotech			
CPP Distance (0-1)	-0.0551**	-0.0429*	-0.0302	-0.0178
	(0.0221)	(0.0217)	(0.0198)	(0.0194)
CPP Distance (0-1) x Frontier (0/1)	-0.396***	-1.251***	-1.091***	-0.972***
	(0.0311)	(0.292)	(0.250)	(0.216)
Observations	204,287	204,287	204,287	204,287
R-squared	0.439	0.443	0.444	0.444
	Panel B: Dependent Variable is Any Biotech Transfer			
CPP Distance (0-1)	-0.0235**	-0.0223**	-0.0174*	-0.0127
	(0.00990)	(0.0101)	(0.00941)	(0.00905)
CPP Distance (0-1) x Frontier (0/1)	-0.250***	-0.335***	-0.346***	-0.324***
	(0.0139)	(0.0709)	(0.0624)	(0.0532)
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 Distance (0-1)	-1.063***	-0.950***	-1.013***	-0.733**
	(0.358)	(0.328)	(0.309)	(0.356)
CPP Distance (0-1) x Frontier (0/1)	-0.152	-0.750*	-0.226	-0.893**
	(1.205)	(0.435)	(0.508)	(0.436)
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 secification is noted at the to 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.

Before proceeding, we probe the sensitivity of the baseline estimates. We first reproduce our results under different measurement strategies for ecological differences. Column 1 of Table A1 reproduces our baseline estimates for reference. In column 2 , we show our results are stable using the Jaccard (1900, 1901) distance metric. In column 3, we show the same using an alternative CPP distance classification that counts CPPs as "present" if CABI lists any information about them, including whether they have been eradicated in the past.[33] In Appendix C.1, we discuss how we can use the CABI data to identify possible species invasions in recent history, which could be affected by crop-level trade or connectedness between countries, and show the stability of our results to excluding all invasive CPPs. We next 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. In column 4 of Table A1, 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 (for instance, via crop-specific trade costs). In columns 6 and 7, we exclude from the sample origin-destination pairs within 1000km or 2000km of each other respectively. Each exercise produces stable results. Finally, Table C2 reports results after controlling for several non-CPP measures of ecological dissimilarity across crops and country-pairs, and again the estimates are very similar. This analysis is discussed in detail in Appendix C.2.

Finally, we report estimates of (4.2) in Table 2. The blended, extensive, and intensive margin effects are reported in Panels A, B, and C, respectively; and our definitions of the frontier as the US, $T_1(k)$, $T_2(k)$, and $T_3(k)$ are used in columns 1-4. In the extensive and blended-margin specifications, we find strong, significant evidence of $\beta_2 < 0$; in the intensive-margin specification, we have consistently negative point-estimates, which are statistically significant in two of four cases. Together, these estimates suggest that the effect of CPP distance on technology diffusion is considerably larger for research intensive origins. For example, in columns 2-4 of Panel A, the marginal effect of CPP distance on the asinh transformation of technology diffusion is approximately thirty times larger for frontier origin markets. These estimates imply that high ecological dissimilarity to the frontier can leave a country with little or no appropriate technology produced in the frontier.

5. Main Results: Production

The previous section established that potential inappropriateness in the form of ecological difference inhibits technology transfer. We now study how ecological differences relative to frontier innovators affect global production and specialization. Our results will allow us to quantify the total effects of inappropriateness via the model in Section 7.

[33] Potential eradications are quite rare. The number of CPP-country-crop triads increases by under 3% when using the "broad" CPP presence classification.

5.1 Data and Measurement

5.1.1 Agricultural Production

We compile data on crop output, trade (imports and exports), 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.[34] The Brazilian data are from the 2017 round of the Censo Agropecuario, and they cover 49 crops. The Indian data are from the ICRSAT Database and constructed from the 2015 Agricultural census, and they cover 20 states and 20 crops.[35]

5.1.2 Distance to 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 two more heuristic but parsimonious strategies to measure each country's ecological distance from the *frontier technology producers*, as introduced in Section 4.2.

The first, and simpler, strategy is to assume that the United States produces the frontier technology for all crops and set $\text{CPPDistFrontier}_{k,\ell}^{\text{US}} = \text{CPPDistance}_{k,\ell,\text{US}}$. In the model, this method is exactly correct if the United States were the sole producer of technology, as in the unipolar example of Section 2.3; 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 variiety releases in the UPOV data. Given a set $T_N(k)$ of the N top countries for k-variety releases, we calculate

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

where $\text{CPPDistance}_{k,\ell,\ell'}$ is our main bilateral measure defined in Equation 3.2. This method picks up geographic variation in technological leadership, but relies on cross-national comparisons of variety release intensity. In the model, this can be mapped to case in which only the countries $\ell \in T(k)$ produce technology for k, productivity $\Theta(k,\ell)$ is linearly approximated around a steady state with $\delta(k,\ell,\ell') \equiv 0$ for all $\ell' \in \Theta(k,\ell)$, and $\text{ShareVarieties}_{k\ell'}$ equals the fraction of farms that would use ℓ' technology if all technology were equally appropriate. For our main results, we use $N = 2$.

These strategies for defining frontier innovators are further motivated by the results in Table 2, showing that CPP distance to the US or countries in $T(k)$ have a disproportionate negative effect on biotechnology diffusion. In fact, in some specifications, CPP distance to countries *outside* this set of

[34] We chose these countries because they are the two developing countries for which we have state-level information on CPPs and thus are able to conduct our entire analysis at the sub-national level.

[35] For a description of the ICRSAT data, see here: http://data.icrisat.org/dld/src/about-dld.html.

frontier countries has no effect on technology diffusion (e.g. columns 2-4 of Panel A).

In practice, the two measures of CPPDistFrontier have a similar distribution across crops and space and a strong positive correlation with one another. In a univariate regression of the former on the latter, the coefficient 0.93 and R^2 is 0.91 (Figure A5). The underlying reason is that our identified technological leaders, in the majority of cases, are subsets of the US, Canada, and temperate countries in Western Europe. This foreshadows the fact that our main findings are similar using either measure.

5.1.3 Direct Effects of the Local Environment

In the model, the relationship between ecological distance and production was correctly specified conditional on measurements of the parameter $\omega(k, \ell)$, local innate suitability for growing crop k in country ℓ (see 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 and Donaldson, 2012; 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). While this method parsimoniously summarizes agronomic predictions of innate suitability, it is only available for 34 of our 180 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, and soil acidity, clay content, silt content, coarse fragment content, and water capacity at the crop-by-country level, by averaging these variables over the historical planting locations from the *EarthStat* database. Appendix C.2 describes these data in more detail.

5.2 Empirical Model

We estimate the following model which is equivalent to Equation 2.7 in Proposition 2:

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

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). Depending on the specifica-

Table 3: CPP Distance Reduces Agricultural Output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Distance to US				CPP Distance to Estimated Frontier Set			
CPP Distance (0-1)	-9.122***	-9.872***	-9.155***	-8.081***	-6.963***	-5.347***	-7.036***	-6.139***
	(1.152)	(2.834)	(0.596)	(0.629)	(0.934)	(0.632)	(0.446)	(0.492)
log(FAO-GAEZ-Predicted Output)		0.298***				0.351***		
		(0.0812)				(0.0501)		
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
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,915	2,353	6,920	6,069	6,693	2,353	6,696	5,903
R-squared	0.600	0.617			0.600	0.609		

Notes: The unit of observation is a state-country pair. Columns 1-4 use CPP dstance to the US and columns 5-8 use CPP dstance to 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 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, growng 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.

tion, we include a subset of proxies for innate suitabililty in the vector $\Omega_{k,\ell}$. 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 (5.2) are reported in Table 3. In columns 1-4, CPP distance to the frontier is parameterized as crop-specific distance to the US and, in columns 5-8, it is parameterized as crop-specific distance to the crop-specific estimated frontier country set. In both cases, we estimate a large and significant negative coefficient. Our estimates imply that a one standard deviation in increase in CPP distance from frontier countries reduces output by roughly 0.5 standard deviations.

The specifications in columns 1 and 5 only include the CPP distance measure, along with crop and country fixed effects, on the right-hand side of the regression. The remaining columns show the stability of these estimates under each of our control strategies for local suitability. In columns 2 and 6, we include the FAO 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 effectfts. 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.[36] Results are stable in each variation of the control strategy.

Testing an additional prediction of Proposition 2, Table A6 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 indistinguishable magnitudes relative to our main estimates for production up to statistical precision. Economically, this implies that agricultural allocations are optimally adjusted to eliminate cross-crop differences in marginal products, and that the footprint of productivity differences is therefore revealed by specialization rather than "efficiency" metrics like yields.

Table A7 investigates the impact of CPP distance on additional features of agricultural production and output. First, we document that CPP distance to the frontier is significantly negatively correlated with crop-specific exports (column 2), and positively (albeit insignificantly) correlated with crop-specific imports (column 3). Second, we document that CPP distance to the frontier is significantly positively correlated with producer price volatility. The appropriateness of frontier technology might not only raise average productivity but also increase producers' ability to withstand periodic negative productivity shocks.[37] The negative relationship with producer price volatility is similar even after holding total output fixed (columns 5 and 7).

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 the best biotechnology firms for producing seeds 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 tantamount to being ecologically "bad." Indeed, in the US there is a long history of science and technology development to confront crop disease and the challenging pathogen environment (Olmstead and Rhode, 2008).[38] 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, 2018).

Our results, on the other hand, suggest that the indirect role of geography via production technology, or the endogenous determination of "good geographies" that resemble technological leaders', is an important determinant of production patterns. In subsequent analysis, Section 6.1 and Appendix C.5 will document that historical *changes* in the focus of biotechnology research affect changes in technology adoption and production, further suggesting that our estimates are not driven by a static omitted variable, and that "good geographies" change with the focus of innovation.

[36] Thus, all controls vary at the country-by-crop level. When we include all aforementioned controls, the LASSO pool contains 3.935 potential covariates. Throughout, we include crop and country fixed effects in the LASSO amelioration set.

[37] Bad insect outbreaks are a commonly cited example. See Stone (2020) for a discussion of recent locust outbreaks in East Africa and their economic impact.

[38] In fact, during its early history, the US government made a major effort to recover plant varieties from around the world in order to increase farm productivity and promote agricultural resilience, and these foreign varieties were distributed via the early Post Office (Kloppenburg, 2005).

5.4 Sensitivity Checks

5.4.1 Additional Controls and Measurement

The results in Table 3 are very similar after including a range of additional controls. Table A4 documents that the results are very similar including crop-by-continent fixed effects, which allow us to focus on even more geographically precise variation in the inappropriateness instrument. Table A5 shows that results are similar after controlling for a broad spectrum of country-level characteristics, all interacted with crop fixed effects, which rules out confoundedness with crop-specific effects of other determinants of income.[39] The results are also similar after purging the CPP distance measure of variation driven by invasive species (Appendix C.1) and accounting dissimilarity to the frontier in non-CPP ecological characteristics (Appendix C.2). Moreover, inappropiateness measured using non-CPP ecological characteristics also depress technology diffusion also reduces output; however, this effect is independent from and smaller than the effect of CPP distance (Table C3).

5.4.2 Falsification Tests

If our main estimates capture the impact of inappropriateness on technology diffusion and hence productivity, then we would expect to find a limited or absent relationship between CPP distance to countries that are *not* centers of biotechnology development and productivity. To investigate this, we re-estimate Equation 5.2, replacing $\text{CPPDistFrontier}_{k,\ell}^{US}$ with CPP distance to each country on the world; this generates a series of coefficient estimates $\hat{\beta}^{\ell}$, one for each country. That is, we estimate:

$$y_{k,\ell'} = \beta^{\ell} \cdot \text{CPPDistance}_{k,\ell'}^{\ell} + \chi_{\ell'} + \chi_k + \Omega_{k\ell'}'\Gamma + \varepsilon_{k,\ell'}$$

for all ℓ. Figure A4 reports histograms of estimates of the $\hat{\beta}^{\ell}$, from specifications that do not include CPP distance to the US as a control (Figure A4a) as well as from specifications that do (Figure A4b). In both cases, the coefficient on CPP distance to the US, marked with a red, 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 clustered around zero, especially conditional on CPP distance to the US.

Moreover, the $\hat{\beta}^{\ell}$ are significantly negatively correlated with country-level biotechnology development measured in the UPOV database. We estimate:

$$y_{\ell} = \xi \cdot \hat{\beta}^{\ell} + \varepsilon_{\ell}$$

where the dependent variable is either the number of varieties development in ℓ in the UPOV data, or an indicator that equals one of country ℓ enforces intellectual property protection for plant biotechnology. These are two proxies for the R&D intensity of country ℓ. Table A8 reports estimates

[39] These country-level characteristics include income, openness to trade, inequality, specialization in agriculture, agricultural productivity, and R&D intensity.

Table 4: CPP Distance Reduces Agricultural Output: State-by-Crop Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Distance to US				CPP Distance to Estimated Frontier Set			
CPP Distance (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 dstance to the US and columns 5-8 use CPP dstance to 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 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, growng 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.

of ξ. The coefficient estimates are negative and significant, suggesting that CPP distance 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.

5.5 Within-Country Estimates: Brazil and India

Finally, we exploit *state*-level information on pest and pathogen presence for both Brazil and India, along with the fact that both countries report detailed data on crop production at the state-level, to measure the effects of inappropriateness at a sub-national level. Our estimation framework is:

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

where now s indexes states and $\ell(s) \in \{\text{Brazil, India}\}$. 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. Thus, we estimate a qualitatively different parameter from the preceding analysis but also fully absorb potential unobservable features in the country-by-crop level analysis.

Our estimates of Equation 5.3 are displayed in Table 4, which follows the exact same structure as the baseline country-by-crop estimates in Table 3. Despite the inclusion of *country-by-crop* fixed effects, we find negative and significant estimates that are very similar in magnitude to our country-

by-crop results. 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 5), 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 A6). Together, these estimates suggest that the (in)appropriateness of technology not only shapes productivity differences across countries, but also shapes productivity differences across regions *within* countries, which is responsible for a large share of global inequality (Acemoglu and Dell, 2010).

6. Case Studies: Inappropriateness and Technology Adoption

The empirical results of Sections 4 and 5 quantified the impact of CPP mismatch on technology diffusion and its consequences for production and specialization. In this section, we provide additional empirical evidence about an intermediate prediction: that inappropriate technology is less likely to be adopted by farmers.[40] To do this, we home in on the geographically heterogeneous penetration of improved high-yielding varieties developed in the Green Revolution, and the relatively low usage of frontier agricultural technology in modern Africa.

6.1 High-Yield Varieties in the Green Revolution

The Green Revolution was a coordinated international effort, backed by philanthropic organizations like the Rockefeller Foundation, 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 (CGIAR), an organization charged with coordinating international crop development for the poor world (Evenson and Gollin, 2003b).

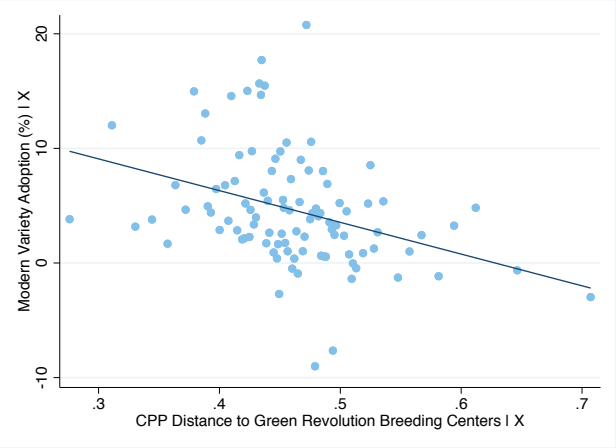
Modern variety adoption and productivity growth during this period, however, still differed markedly across crops and countries (Evenson, 2005). One potentially important source of this heterogeneity, highlighted by scholars, is that varieties developed at the IARCs were inappropriate in places that are ecologically dissimilar from the countries in which the IARCs were located (Binswanger and Pingali, 1988; Lansing, 2009; Pingali, 2012). Lansing (2009) provides an in-depth case study of the detrimental impacts of the introduction of Green Revolution rice varieties and farming practices in Bali, where local practices had evolved to keep the local pest population at bay. The shift to Green Revolution technology precipitated widespread crop failures, driven by pest outbreaks.[41]

[40] A formal articulation of this prediction is given in Corollary 1 in Appendix B.4.

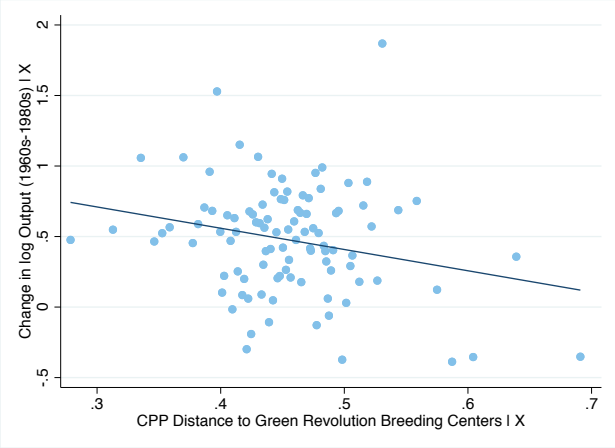
[41] Reynolds and Borlaug (2006), from an IARC's perspective, document the significant challenges faced by CIMMYT to develop semi-dwarf wheat that would thrive outside of Mexico. CIMMYT's best success, by its own testimony, came in the instances where close, decades-long coordination with foreign research organizations was possible, like CIMMYT's long-standing partnership with Brazil's EMBRAPA.

Figure 4: Inappropriateness and the Efficacy of the Green Revolution

(a) Modern Variety 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 $\text{CPPDistGreenRevolution}_{k,\ell}$ 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.

To 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 centered. The set of crops, along with their corresponding IARCs and countries, is reported in Table A9. Using this information, we compute a measure of CPP distance to centers of Green Revolution breeding at the crop-by-country level:

$$\text{CPPDistGreenRevolution}_{k,\ell} = \sum_{\ell'} \text{CPPDistance}_{k,\ell,\ell'} \cdot \mathbb{I}\Big\{\text{IARC for } k \text{ is in } \ell\Big\} \tag{6.1}$$

where $\mathbb{I}\Big\{\text{IARC for } k \text{ is in } \ell\Big\}$ is an indicator that equals one if Green Revolution breeding of crop k was centered in country ℓ'. For example, IRRI in the Philippines was the main IARC for rice, so in all countries CPP distance for rice is computed as CPP distance to the Philippines.

We first study the relationship bewteen $\text{CPPDistGreenRevolution}_{k,\ell}$ and modern variety adoption at the crop-by-country as reported by Evenson and Gollin (2003a,b). We regress the percent of area devoted to high-yield varieties in 1980-85, a representative cross-section after the bulk of Green Revolution research was instigated, on $\text{CPPDistGreenRevolution}_{k,\ell}$ and absorbed effects at the location and crop-by-continent ($k \times c(\ell)$) level:

$$\text{HYVAdoption}_{k,\ell,1980} = \beta \cdot \text{CPPDistGreenRevolution}_{k,\ell} + \chi_\ell + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \tag{6.2}$$

Our sample is the 8 crops in Table A9 intersected with the 85 low-income countries in the Evenson and Gollin (2003a,b) data. Our main findings are summarized in Figure 4a, which shows a binned scatter plot of our estimates of Equation 6.2 net of fixed effects. Our estimate of $\hat{\beta} = -26.62$ (SE: 9.15) implies that the 75th percentile crop-country pair had 5 percentage points lower HYV penetration than the 25th percentile in 1980, 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 jumps to $\hat{\beta} = -96.20$ (SE: 27.17), implying a 18 percentage point difference between the 75th and 25th percentiles relative to a mean of 14% (see Table A10).

We next directly study the impact of this heterogeneous adoption on production and specialization by adapting our empirical framework from Section 5. We first study how CPP distance from Green Revolution centers affected production *growth* from the 1960s to the 1980s, the period when the majority of Green Revolution research took off. We estimate the following regression model:

$$y_{k,\ell,1980s} - y_{k,\ell,1960s} = \beta \cdot \text{CPPDistGreenRevoluion}_{k,\ell} + \tau \cdot y_{k,\ell,1960s} + \chi_{\ell} + \chi_{k,c(\ell)} + \varepsilon_{k,\ell} \tag{6.3}$$

where the dependent variable is the *change* in (log of) crop-level output between the 1960s and the 1980s. We continue to restrict attention to the sample studied in the adoption model. This model 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 relative to the relevant set of innovating countries.

Our findings, summarized as a binned scatter plot in Figure 4b, are that production shifts away, in relative terms, from crop-location pairs less ecologically similar to Green Revolution hubs. Our coefficient estimate $\hat{\beta} = -2.64$ is about 1/3 of our previously estimated point estimate for the effects of modern inappropriateness relative to the technological frontier.[42] Table A11 documents that the relationship between CPP distance to Green Revolution breeding centers and changes in production is restricted to the period 1960-1980, the height of the Green Revolution (columns 1-3); the effect is apparent in Asia, Africa, and South America, but not in Europe, which was not an intended recipient of Green Revolution technology (columns 4-7).

Taken together, our findings illustrate how geographical inappropriateness shaped the adoption and consequence of critical technological breakthroughs in the 20th century. In Section 7, we will address via model counterfactuals the follow-up question of how plausible "geographies" of future breakthroughs would influence global productivity.

6.2 Technology Adoption in Sub-Saharan Africa

We next study how inappropriateness affects production on the world's poorest farms in modern times. Our area of focus for this analysis in sub-Saharan Africa, which has received substantial attention for attention for the low penetration of agricultural technology in spite of ostensible benefits (see,

[42] Table A10 reports summarizes the estimates for both of our regression models.

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 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, and the LSMS-ISA also provides the coordinates of the approximate location of each farm.[43] Our key dependent variable of interest is farm-by-crop information on the use of improved seeds (i.e., not locally bred or "traditional" varieties). We construct an indicator variable for each crop grown in each farm if improved seed varieties are used. In total, we have data on approximately 120,000 crop-farm pairs across all eight countries.

Our main estimating equation is:

$$\text{ImprovedSeed}_{k,z} = \beta \cdot \text{CPPDistFrontier}_{k,\ell(z)} + \chi_{\ell(z)} + \chi_k + \varepsilon_{k,z} \tag{6.4}$$

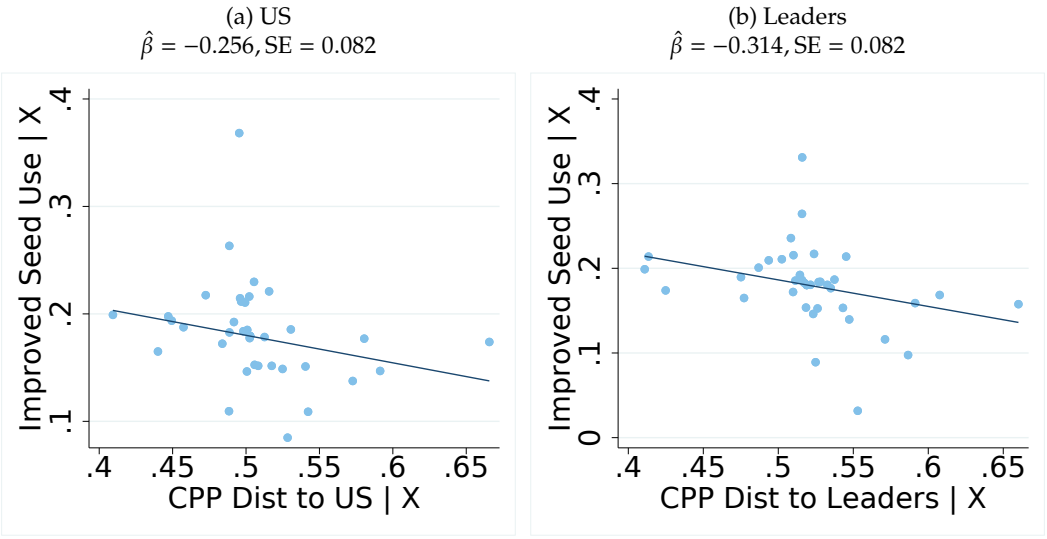
where k continues to index crops and z indexes farms in the LSMS-ISA data. The dependent variable is an indicator that equals one if farmer z uses an improved seed variety for crop k. χ_k denote crop fixed effects and $\chi_{\ell(z)}$ denote country fixed effects, included in all specifications. If the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

Our main findings are summarized in Figure 5. The two panels show results based on our two specifications for CPP distance to the frontier (using the US and the estimated frontier set). In both cases we find a significant negative relationship between adoption and CPP distance. The estimates of column (a) 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%. Appendix Table A12 shows the estimates are robust to a number of additional specifications, including flexible controls for location within countries, state fixed effects, and alternative constructions of CPP distance.

These estimates suggest 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.

[43] To preserve farmer anonymity, the LSMS-ISA provides the latitude and longitude of each survey cluster rather than unique coordinates for each household. To keep a consistent sample across specifications, we restrict our analysis to households in which the cluster coordinates were included in the data set.

Figure 5: Inappropriateness and Technology Adoption in Africa



Notes: Each sub-figure displays binned partial correlation plots, after absorbing country and crop fixed effects, in which the dependent variable is the listed CPP distance and the dependent variable is an indicator for using improved seeds. Standard errors are clustered by country-crop.

7. Inappropriate Technology and Productivity: Present and Future

In this Section, we use our empirical estimates from Section 5 in combination with the model to study how the inappropriateness of technology and existing ecological bias of the global innovation system affects global productivity. We first study the level and distributional effects of "removing inappropriateness" in the observed equilibrium (Section 7.1). We next use our model to study counterfactual scenarios of targeted research in a Second Green Revolution (Section 7.2), realignment of agricultural research toward emerging markets (Section 7.3), and global movement of crop pests and pathogens due to climate change (Section 7.4).

7.1 The Total Causal Effect of Inappropriateness

How does the inappropriateness of frontier technology affect the global distribution of agricultural productivity? To pose this question more precisely and provide a quantitative answer, we return to the case of the model in Section 2.3 with a single frontier innovator producing technology, which is simple to link to our empirical results. In this model, the productivity of each crop in each country is log-linear in CPP distance to the Frontier with slope $-\overline{B}$ and maximum value $\log \overline{\Theta}(k, \ell)$:

$$\log \Theta(k, \ell) = \log \overline{\Theta}(k, \ell) - \overline{B} \cdot \text{CPPDistFrontier}(k, \ell) \tag{7.1}$$

Our specific thought experiment to capture "removing inappropriateness," as foreshadowed in Section 2.3, is to set $\Theta(k, \ell) = \overline{\Theta}(k, \ell)$. This can be interpreted as making frontier technology as productive as possible, or introducing an equal knowledge spillover toward research on local and non-local CPPs. We think of this experiment as a simple, albeit non-realistic, way to understand how the observed geography of research and CPP threats determines observed productivity.

7.1.1 Methods

To link our empirical estimates with the model, we first reinterpret Equation 2.7 in Proposition 2 using the structure of Equation 7.1, our reduced form empirical estimating equation. The regression of production on CPPDistFrontier (Equation 5.2, Table 3) identifies $\beta = -\eta\overline{B}$, where η is the elasticity of supply with respect to productivity changes (or, more primitively, the Fréchet shape parameter). Isolating the productivity effect of inappropriateness therefore involves correcting our reduced-form estimate of β, which conflates productivity effects and supply responses, for the upward-sloping supply curve. Our strategy for doing so is to obtain an external estimate of the supply elasticity ($\eta = 2.46$) from Costinot et al. (2016), who study productivity changes and re-allocation in global agricultural production in the same Fréchet discrete choice model. These authors' estimate, in a nutshell, is what is required to explain the relationship between agronomically measured productivity (from the FAO-GAEZ model) and observed planting patterns at the plot level in the modern world.[44,45] Plugging in this estimate, our baseline estimate of $\beta = -6.96$ relative to the estimated technological frontier (column 5 of Table 3) translates into an estimate of $\overline{B} = 2.83$, in (approximate) units of percent productivity per basis point of CPP distance.

Next, we observe that, conditional on an estimate of the supply elasticity η, the crop-by-location productivity $\Theta(k, \ell)$ is identified up to scale from data on planted area by crop.[46] The scaling factor is total revenue productivity in the country, which we denote $\Xi(\ell)$ in our model. We use estimates of total agricultural revenue and land area from Fuglie (2012, 2015), again averaged from 2000 to 2016, to calculate this in the data.[47] Our main object of interest in the counterfactuals is $\overline{\Xi}(\ell)$, country-level revenue productivity after removing inappropriateness.

Building on this foundation, we consider three variants of the calculation, each of which is detailed in Appendix B.5. The first is a *first-order* calculation akin to that in Equation 2.12 of Section 2.3, under fixed prices. This a simple heuristic interpretation ("the productivity effect times the average CPP

[44] More precisely, these authors' strategy fits model predictions for plot level (about 50-square-kilometer-size) crop choices, aggregated across countries, to match country-level planting patterns.

[45] Sotelo (2020), studying Peruvian agriculture, finds a very similar estimate of $\eta = 2.06$. Using this smaller value would increase our implied estimates for the productivity consequence of inappropriateness, and therefore inflate all of our causal estimates by approximately a factor of $2.46/2.06 = 1.19$.

[46] The model suggests that an equivalent method is to use production in value terms. We favor using areas because it avoids the need for data on local prices. Consistent with our analysis in Section 5, we use FAOSTAT data averaged from 2000 to 2018.

[47] A final step, which matters only for our model calculation with flexible prices and hence meaningful "interaction" between production in each countries, is the physical size of each country and its agricultural land area. We use the agricultural area estimates of the Fuglie (2012, 2015) dataset to make this adjustment.

distance"), but does not account for reallocation across crops. The second is a fully non-linear calculation, also under fixed prices, which will naturally exaggerate the upside (and dampen the downside) of productivity changes by allowing for reallocation across crops. The third is a non-linear calculation with equilibrium prices, which we model as separable and identical for each crop with elasticity ε:

$$\frac{\overline{p}(k)}{\hat{p}(k)} = \left(\frac{\overline{Y}(k)}{\hat{Y}(k)}\right)^{-\varepsilon} \tag{7.2}$$

To calibrate these demand curves, we use the average value estimated by the US Department of Agriculture for the price elasticity of global food demand, yielding $\varepsilon = 0.35$ (Regmi and Seale, 2010). The additional adjustment of prices recognizes that the natural hedge via terms of trade should dampen both gains and losses in response to productivity shocks.

7.1.2 Results

Figure 6 summarizes our main findings from each aggregation method via one-dimensional summary statistics of productivity levels and disparities. The lower panel shows the average percent loss in agricultural productivity due to inappropriateness. We obtain similar estimates of a 55% loss from the first-order and non-linear methods before incorporating price changes, which suggests a limited role for production reallocation.[48] An intuitive explanation is that within-country, across-crop variation in distance to the frontier, while essential for our identification strategy, is much smaller than overall across-country variation in inappropriateness. We find slightly smaller effects (41%), as expected, when taking into account the terms of trade hedge.

The top panel shows the impact of inappropriateness on international disparities in agricultural productivity; in particular, we estimate the percentage widening of the inter-quartile range of the revenue productivity (per unit land) distribution.[49] By this metric, inappropriateness explains between 10 to 17% of observed agricultural productivity gaps. This is a first hint that, as anticipated in our motivating examples, some of the largest consequences of inappropriateness are found in the world's least productive agricultural areas.

We next more closely explore the distributional implications of our findings. The left panel of Figure 7 shows the distribution of productivity losses by country as a histogram, focusing on the full-model, flexible-price calculation. The largest losses from inappropriateness are concentrated in Africa and Asia, while the smallest are in Europe. The right panel shows directly the relationship between our estimated productivity losses and measurements of present-day revenue productivity. These variables are negatively correlated, with a coefficient estimate of -0.018 and t-statistic (het-

[48] Were it not for any numerical inaccuracies created by the first-order approximation, the no-reallocation scenario would always over-state losses. A fully non-linear calculation that shuts down reallocation, omitted due to its similarity to the highlighted calculations, confirms this prediction.

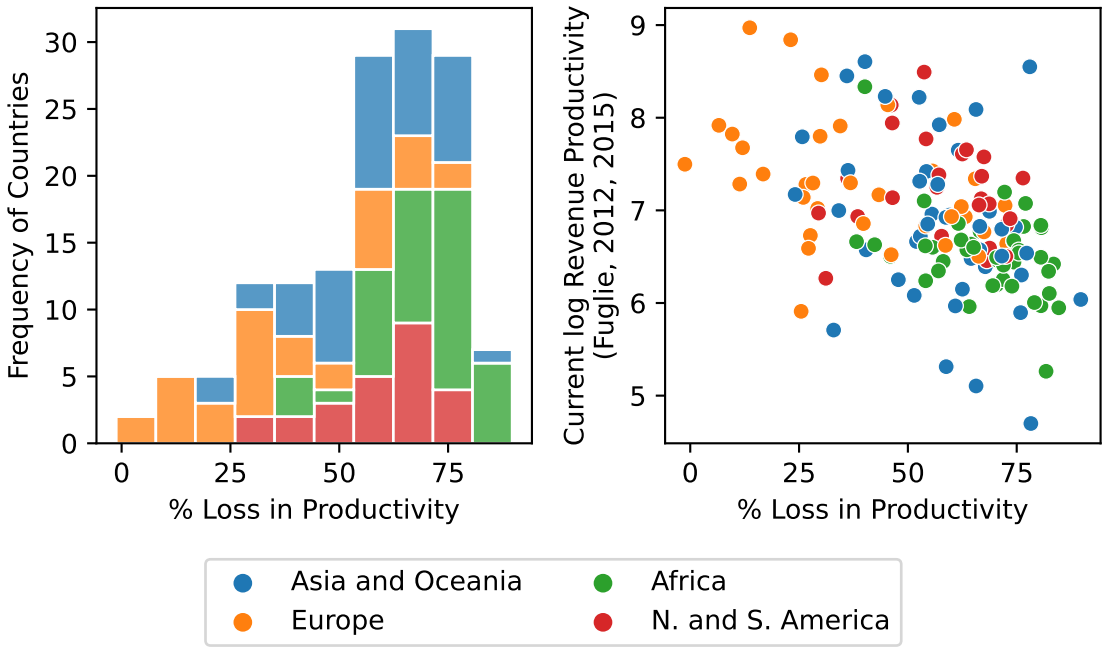
[49] Specifically, let $\overline{\text{IQR}}$ and $\hat{\text{IQR}}$ report this statistic of the cross-country productivity distribution under each scenario. We report $100 \cdot \frac{\overline{\text{IQR}} - \hat{\text{IQR}}}{\overline{\text{IQR}}}$. We prefer the inter-quartile range to other measures of dispersion, like the variance, because it is less sensitive to a few outlier countries.

Figure 6: Total Causal Effects of Inappropriateness



Notes: Bars are standard errors from the Delta Method, using the numerical first-order sensitivity of quantities to the single estimated parameter β. Productivity losses are area-weighted means across countries. The three model scenarios are described in the main text.

Figure 7: Causal Effects of Inappropriateness: Heterogeneity by Location



Notes: The left graph is a histogram of productivity losses from inappropriateness, where colors indicate observations (countries) by continent. The right graph is a scatterplot of productivity losses against observed productivity, with the same coloring scheme.

eroskedasticity robust) of −6.1. Thus, we estimate the inappropriateness has the largest, negative effects on productivity in precisely the countries that are least productive today.[50]

These results, taken together, put into sharp relief the inequality created by the interaction of ecological heterogeneity and the global innovation system. Neglected agricultural ecosystems, like neglected tropical human diseases (Hotez et al., 2007), are concentrated in specific and predominantly poor parts of the world. These regions are unproductive today, and kept unproductive due to an absence of appropriate technology or incentives to develop it. By implication, our framework suggests that the main short-run remedies are policies that seed the ground for local biotechnological research.

7.2 Mapping a Second Green Revolution

The Green Revolution focused research investment on a specific set of tropical countries in order to develop varieties that would increase output, especially among the world's least productive countries. Our model underscores the importance of such local targeting of technology and, moreover, provides a quantitative framework to study how one may target a "Second Green Revolution" that is as appropriate, and productivity enhancing, for the world as possible.

To interpret and answer this qusetion, we consider the effects for each crop k, country ℓ, and candidate research hub ℓ', of shifting each country's productivity to the counterfactual level

$$\log \Theta(k, \ell; \ell') = \log \overline{\Theta}(k, \ell) - \overline{B} \cdot \text{CPPDistance}(k, \ell, \ell') \tag{7.3}$$

where $\log \overline{\Theta}(k, \ell)$ and $\overline{B}$ are calibrated as described in the previous section. The thought experiment is to shift the current research frontier to location ℓ', holding fixed the maximum attainable productivity $\log \overline{\Theta}(k, \ell)$.[51] We next use area-weighted averages to aggregate effects across crops within a country and across countries under the first-order approach.[52] This allows us, under the running thought experiment, to identify locations for breeding locations that maximize output in specific countries or groups of countries.

In Table 5, we report our results for the set of crops that were the focus of our analysis of the historical Green Revolution. Columns 2 and 4 report the two countries where breeding research would increase global output by the most based on reducing CPP mismatch, and columns 3 and 5 show the corresponding effects on global agricultural productivity in log points times 100. Columns 6-10 report the results of the same exercise if we calculate productivity gains only for countries with below median modern productivity.

[50] 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 and t-statistic of -3.7.

[51] Whether a fixed dollar investment in a research center in India versus France has the same research output, for example, is beyond the scope of our analysis. Our results can be understood as determining the international return on a research investment of a fixed domestic *benefit* rather than fixed domestic *cost*.

[52] The first-order calculation, in addition to being accurate according to our findings of the previous section, allows for a simple interpretation of the exercise as minimizing "importance-weighted CPP Distance."

Table 5: Inappropriateness-Minimizing Centers for Modern Agricultural Innovation

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Crop	Sites Chosen to Minimize Global Inappropriateness				Sites Chosen to Minimize Inappropriateness in Countries with Below Median Productivity			
	Best Site	% Change in Productivity	Second Best Site	% Change in Productivity	Best Site	% Change in Productivity	Second Best Site	% Change in Productivity
Wheat	Russia	1.9	Australia	1.5	Russia	4.3	Australia	3.1
Maize	China	3.9	USA	3.8	South Africa	1.7	India	1.6
Sorghum	India	0.8	Nigeria	0.7	India	1.6	Nigeria	1.5
Millet	India	1	South Africa	0.8	India	1.9	South Africa	1.6
Beans	India	1.3	China	1	India	1.8	China	1.2
Potatoes	China	0.4	Russia	0.2	Russia	0.4	Turkey	0.1
Cassava	Nigeria	0.5	Ghana	0.4	Nigeria	1	Tanzania	0.8
Rice	India	6.7	China	6.6	India	7.9	China	5.4

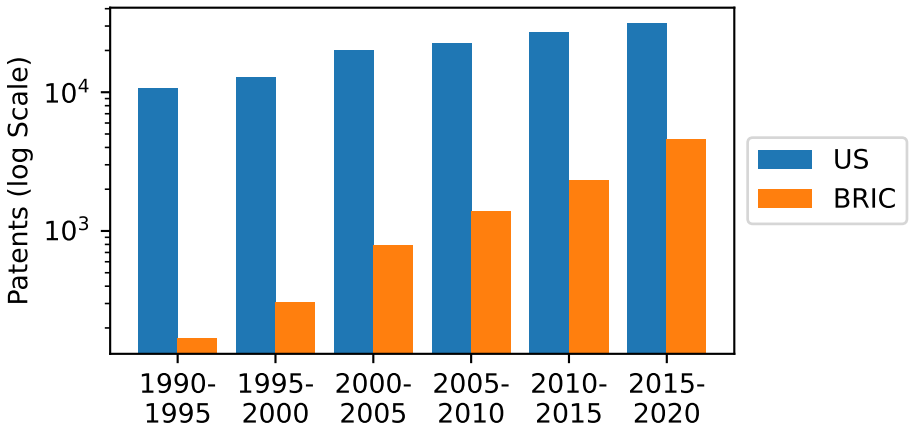
Notes: Column 1 reports the crops included in our analysis of the Green Revolution. Columns 2-5 report the results of our analysis to select the two countries where breeding investment would have the largest positive effect on global output for each crop. Columns 6-9 report the results of our analysis 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.

This analysis, while necessarily somewhat speculative, yields several interesting conclusions. First, the set of countries that increases total versus low-productivity countries' output is similar. This is consistent with our findings in Section 7.1.2 that reducing ecological mismatch would both increase global output and reduce production disparities. More practically, even ignoring barriers to trade, feeding the world with more appropriate technology is consistent with developing technology for the world's poorest. India, the modal country on both lists, was also a key center of historical Green Revolution research for this reason. Second, the findings are consistent with the hypothesis that a lack of breeding in Africa, including during the Green Revolution, holds back global productivity growth (Pingali, 2012). Nigeria, Ghana, South Africa, and Tanzania all emerge as countries where breeding research could have positive global effects on output. Finally, the prominence of China (and, to a lesser extent, Russia) on the lists highlights the role that geopolitics might have played and continue to play in shaping where research takes place. Political connections may limit where governmental or philanthropic organizations can invest in technology development, limiting potential return on investment. The same pattern, however, suggests that there are potentially large opportunities for countries like China, India, and Russia—growing players in global R&D—to market their technology around the world, especially in countries where appropriate technology is lacking in the current innovation equilibrium.

7.3 New Biotechnological Leaders

In the past several decades, the United States and Western Europe have been at the center of global biotechnology development. However, there is reason to believe that the landscape of biotechnology

Figure 8: 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.

research could change in the coming years—and some evidence that this process has already begun.

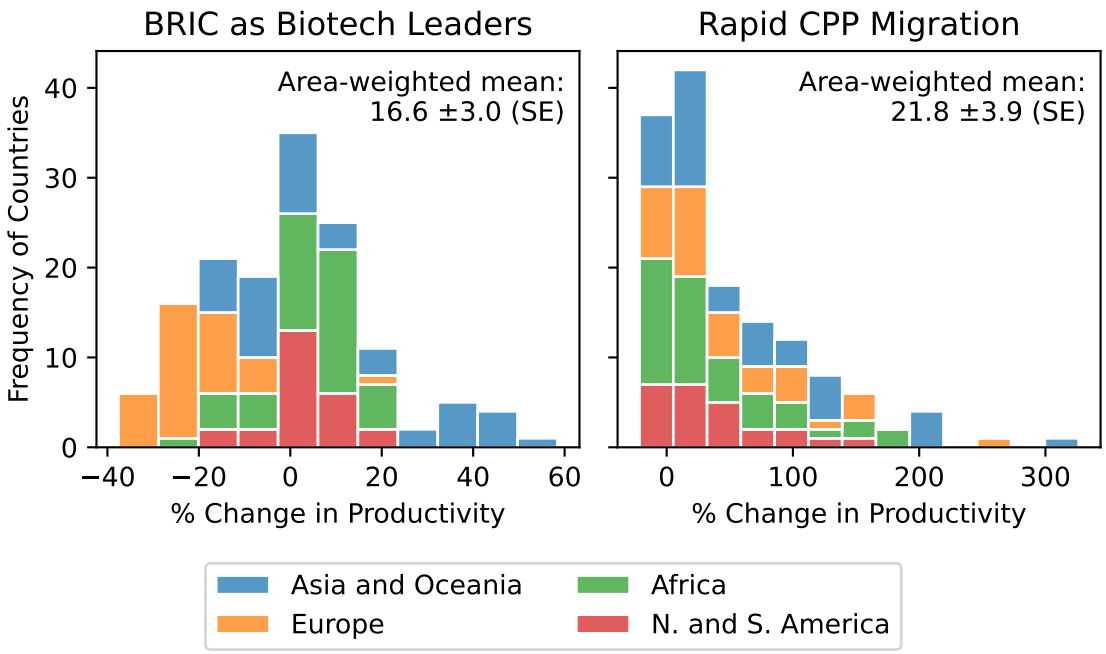
Figure 8 displays the number of patented agricultural technologies over time, relative to the period 1990-1995, comparing technologies developed in the United States to the trend for technologies developed in "BRIC" countries (Brazil, Russia, India, China). While throughout the period, the *level* of innovation in the US is higher than in BRIC countries, the growth rate of agricultural innovation in BRIC countries is striking. The focus on agricultural development is especially acute in China and Russia, where climate change is expected to increase agricultural productivity on large swaths of land (Kiselev et al., 2013).

What might the impact in this shift in the center of global research be on global productivity? If past is prologue, the BRIC countries will focus on developing technologies that combat local threats. The findings of our Second Green Revolution exercise (Table 5) hinted that shift in international focus may be broadly beneficial for boosting global productivity and reducing disparities. Anecdotally, BRIC-nation policymakers have recognized the associated business—and soft power—opportunities. 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.[53]

To operationalize a "rise of BRIC" scenario in our model, we first calculate the CPP distance of

[53]For example, see here: https://www.embrapa.br/en/cooperacao-tecnica/m-boss. The description of the collaboration on the EmBraPA website argues that the "exchange of knowledge and technologies is facilitated due to similarities in their cultures, climate, ecosystems, and agricultural practices."

Figure 9: Productivity Changes in Counterfactual Future Scenarios



Notes: Both graphs are histogram of productivity losses from inappropriateness, where colors indicate observations (countries) by continent. The scenarios are described in the main text.

every country-crop pair to the BRIC research frontier as:

$$\text{CPPDistFrontier}^{\text{BRIC}}_{k,\ell} = \sum_{\ell' \in \text{BRIC}} \frac{\text{Area}(\ell', k)}{\sum_{\ell'' \in \text{BRIC}} \text{Area}(\ell'', k)} \times \text{CPPDistance}_{k,\ell,\ell'} \tag{7.4}$$

In words, we estimate the inappropriateness of BRIC ecology for each crop, weighting each BRIC country by its share of total area devoted to that crop within the BRIC countries.[54] We then, in analogy to the methods of our Second Green Revolution exercise, calculate a counterfactual productivity for each country based on its maximum productivity $\log \overline{\Theta}(k, \ell)$ net of the potential inappropriateness of a BRIC-focused frontier. To take into account the multi-faceted effects of this shock on all crops and global markets, we calculate counterfactuals using our full model with non-linear adjustments and price responses.

The left panel of Figure 9 summarizes our findings in a continent-coded histogram of the implied revenue productivity changes. The average effect is a 17% productivity boost, speaking to the fact that the BRIC countries span more ecological diversity than the existing set of 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 set of technological leaders. From the perspective of the developing world, a shift of

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

innovation investment to the BRIC nations may be a partial, if incomplete, substitute for encouraging purely local technological development.

7.4 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 has accelerated changes in ecological systems themselves, and will continue to do so over the coming decades (Parmesan and Yohe, 2003). In the context of crop pests and pathogens, increases in temperature lead to a systematic, poleward movement (Bebber et al., 2013). In the data, CPPs have moved poleward over the past 50 years by about 135 kilometers (Bebber et al., 2013); while this historic movement is limited, temperature change over the past fifty years is also much more limited compared to projected temperature change over the coming decades. While global temperatures have increased by about 1°C over the past 50 years, in a "worst case" future scenario, temperature is projected to increase by 4.3°C by 2100.[55] This could change the relevant "geography of innovation," by shifting the relevant set of pest and pathogen threats in each country, even if the identity of innovating countries remains fixed.

We can use our model to investigate the impact of projected range shifts on CPP differences across countries and hence the (in)appropriateness of technology. The impact of climate change on the appropriateness of frontier technology across crops and countries is also not clear *ex ante*. If CPP range shifts increase the CPP similarity between a given country and R&D intensive regions, then it might be able to more effectively make use of technology developed in the new equilibrium. However, CPP movement could also reduce the the CPP overlap across countries if, for example, the US inherits several unique CPPs from Central America (or Europe from North Africa), reducing their similarity to other large parts of the world.

To capture this channel, 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. As noted above, the consensus worst case scenario implies a 4.3°C increase in temperature by 2100, and hence a 700 kilometer 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.[56] We then use these data to construct CPPDistFrontier$(k, \ell)^{CC}$ based on ecological dissimilarity to the modern set of frontier innovators, and re-calcluate productivity as in the previous counterfactuals. The right panel of Figure 9 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 directly negative effects of ecological change,

[55] This projection corresponds to Representative Concentration Pathway (RCP) 8.5, a consensus worse-case scenario.

[56] We included manual corrections for countries with non-contiguous territory, like preventing CPP migration from the United States to Russia via Alaska.

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 essential and important topic for further research.

8. Conclusion

We investigate a long-standing hypothesis that the context-specificity of invention—the fact that technology is designed to match the conditions of the high-income countries that develop it and is hence *inappropriate* for application elsewhere—shapes patterns of innovation, technology diffusion, technology adoption, and productivity. Our empirical focus is global agriculture, and we develop a new measure of the inappropriateness of agricultural biotechnology based on the dissimilarity in crop-specific pest and pathogen (CPP) environments across locations. We first show technology development is concentrated in a small set of countries and focused on local pest and pathogen threats. We next show that environmental dissimilarity is a substantial barrier to the international diffusion of crop-specific biotechnology. We finally show that countries move production away from crops for which their CPP dissimilarity to the research frontier is higher.

Combining our estimates with a model of global agricultural production, we estimate that inappropriateness as proxied by CPP mismatch reduces global agricultural productivity by 40-55%, and increases global disparities in the same by 10-15%. Substantial differences in pest and pathogen threats around the world, and innovators' neglect of ecosystem threats in low-income areas, sustains large disparities in access to appropriate technology and, as a result, in productivity. Moreover, changes in the geography of innovation can have large effects on the distribution of appropriate technology, and hence productivity, around the world. We show that the global impact of the Green Revolution was shaped by ecological similarities differences with the key breeding centers, and argue that in the future, changes in the center of global biotechnology development and in ecology due to global warming could shift features of the technological frontier and hence appropriateness of technology around the world. More exploration of these trends, which will define agriculture and technology in the coming century, is an important area for future research.

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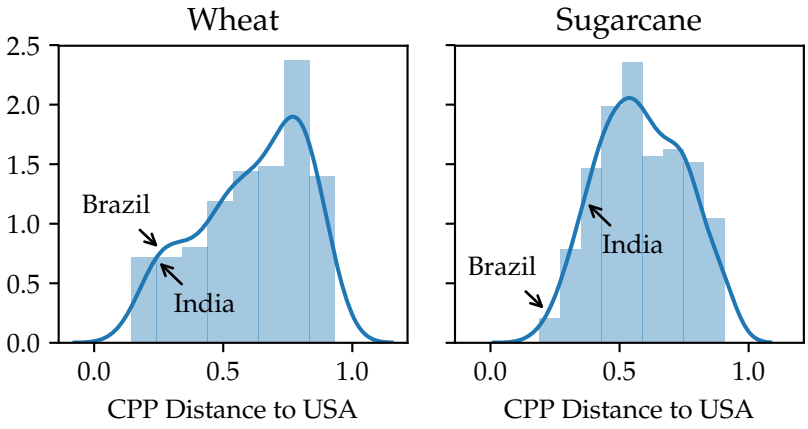
Vidal, J. (2014). Gates foundation spends bulk of agriculture grants in rich countries. *The Guardian*. November 3. Retrieved from: https://www.theguardian.com/global-development/2014/nov/04/bill-melinda-gates-foundation-grants-usa-uk-africa.

Appendix

For Online Publication

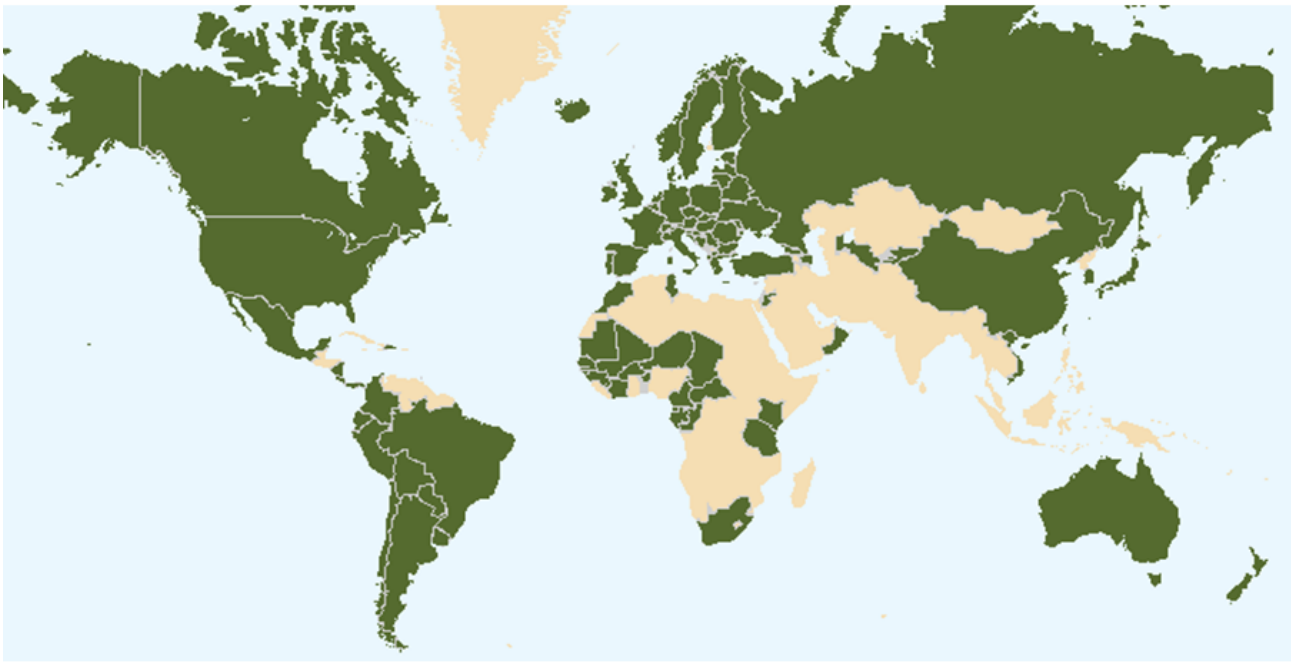
A. Supplemental Figures and Tables

Figure A1: Example of CPP Distance Variation



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

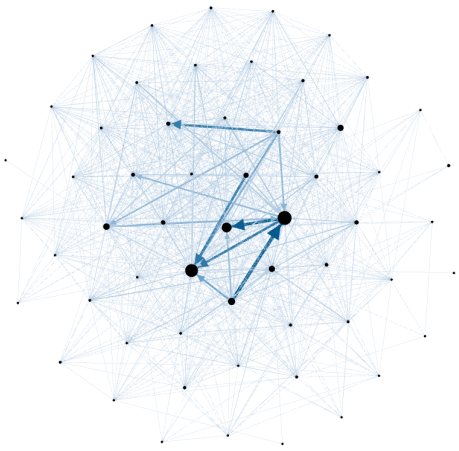
Figure A2: UPOV Compliant Countries



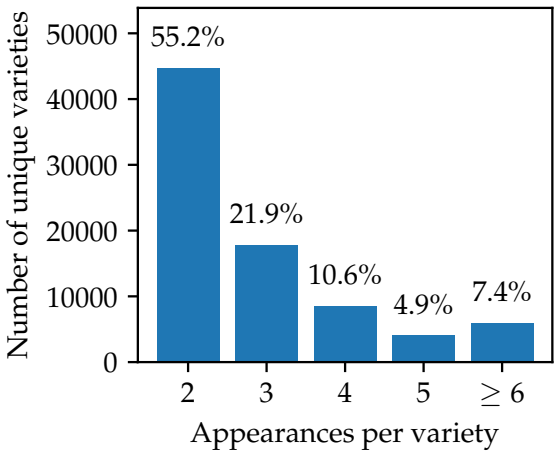
Notes: This figure denotes in green all UPOV member countries. This is the sample of countries for which we have data on biotechnology development and transfer.

Figure A3: Visualizing Variety Transfer

(a) Variety Transfer as a Directed Network

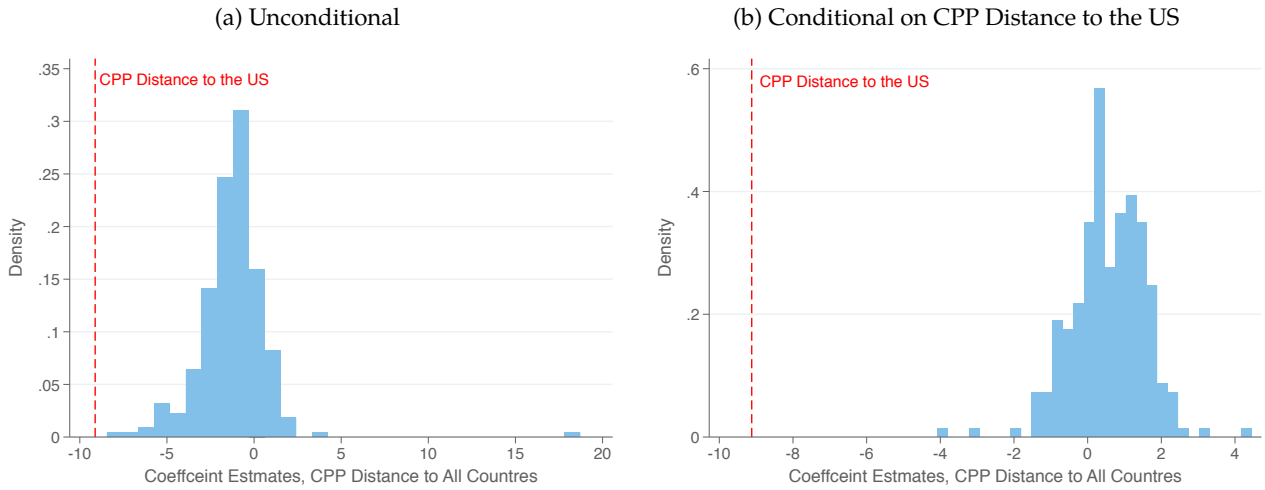


(b) Frequency of Occurance for Varieties



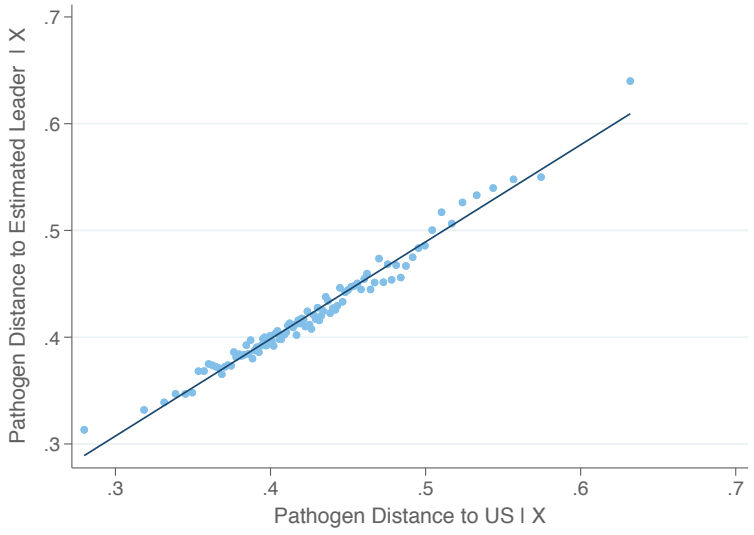
Notes: In (a), each node is a country sized in proportion to its total variety production and each edge is sized and colored in proportion to the number of varieties transferred. In (b), the percentages are in terms of unique varieties.

Figure A4: Falsification Test: CPP Distance to All Countries



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: CPP Distance to the US vs. CPP Distance to Estimated Frontier Set



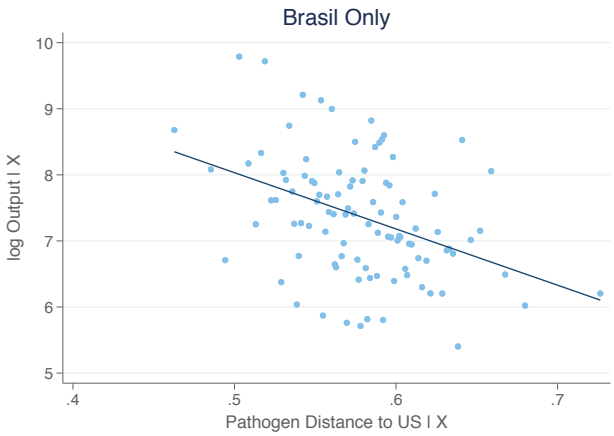
Notes: Coefficient = 0.926 (0.047); t-statistic = 19.61; R^2 = 0.912.

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

(a) India ($\beta = -9.99$ (4.82); $N = 384$)



(b) Brazil ($\beta = -8.51$ (2.72); $N = 1,052$)



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 (A6a) and Brazil (A6b).

Table A1: CPP Distance Inhibits International Technology Transfer: Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Dependent Variable is (asinh) Biotechnology Transfers						
CPP Distance (0-1)	-0.0605**	-0.120**	-0.0848***	-0.0509**	-0.0556**	-0.0434**	-0.0486***
	(0.0241)	(0.0481)	(0.0258)	(0.0231)	(0.0222)	(0.0189)	(0.0169)
	Panel B: Dependent Variable is Any Biotechnology Transfer (0/1)						
CPP Distance (0-1)	-0.0270**	-0.0600***	-0.0373***	-0.0220**	-0.0290**	-0.0215**	-0.0255***
	(0.0109)	(0.0223)	(0.0119)	(0.0103)	(0.0109)	(0.00886)	(0.00842)
	Panel C: Dependent Variable is log Biotechnology Transfers						
CPP Distance (0-1)	-1.072***	-0.831	-0.935**	-1.068***	-0.953*	-1.984***	-2.108***
	(0.361)	(0.529)	(0.363)	(0.367)	(0.472)	(0.495)	(0.657)
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 distiance metric, sample restrictiotn, 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 A2: Patenting Activity Directed Toward Local CPPs

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

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

Table A3: CPP Distance Inhibits International Technology Transfer: R&D Intensive Origins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Biotech Transfer (asinh)			Any Biotech Transfer (0/1)			log Biotech Transfer		
Origin Country Set:	The Untied States	Countries with ≥1 variety developed for crop *k*	Countries that produce crop *k*	The Untied States	Countries with ≥1 variety developed for crop *k*	Countries that produce crop *k*	The Untied States	Countries with ≥1 variety developed for crop *k*	Countries that produce crop *k*
CPP Distance (0-1)	-0.498**	-0.135**	-0.0999***	-0.309***	-0.0604**	-0.0409**	-0.518	-1.072***	-0.902**
	(0.190)	(0.0556)	(0.0362)	(0.0808)	(0.0229)	(0.0155)	(1.273)	(0.361)	(0.345)
Destination Fixed Effects	Yes	-	-	Yes	-	-	Yes	-	-
Crop Fixed Effects	Yes	-	-	Yes	-	-	Yes	-	-
Crop-by-Origin Fixed Effects	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes
Crop-by-Destination Fixed Effects	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes
Origin-by-Destination Fixed Effects	-	Yes	Yes	-	Yes	Yes	-	Yes	Yes
Observations	3,692	100,405	145,238	3,692	100,405	145,238	404	5,791	5,514
R-squared	0.325	0.488	0.465	0.313	0.425	0.407	0.516	0.797	0.802

Notes: The unit of observation is a crop-origin-destination. The dependent variable is noted in the header of each panel. Each specification uses a different set of origin countries, noted 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.

Table A4: CPP Distance Reduces Output: Crop × Continent Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Output							
	CPP Distance to US				CPP Distance to Estimated Frontier Set			
CPP Distance (0-1)	-8.510***	-9.389***	-8.516***	-7.857***	-7.082***	-6.359***	-6.999***	-6.385***
	(1.095)	(2.440)	(0.754)	(0.734)	(0.961)	(1.949)	(0.595)	(0.614)
log(FAO-GAEZ-Predicted Output)		0.239***				0.273***		
		(0.0711)				(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			0.680	0.694		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP dstance to the US and columns 5-8 use CPP dstance to 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 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, growng 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 A5: CPP Distance 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 A6: CPP Distance Reduces Area Harvested

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is log Area Harvested							
	CPP Distance to US				CPP Distance to Estimated Frontier Set			
CPP Distance (0-1)	-9.367***	-11.35***	-9.411***	-7.626***	-7.140***	-7.020***	-7.198***	-5.837***
	(1.168)	(2.706)	(0.572)	(0.621)	(0.940)	(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	6,665	2,268	6,673	5,908	6,459	2,268	6,464	5,748
R-squared	0.613	0.613			0.609	0.603		

Notes: The unit of observation is a country-crop pair. Columns 1-4 use CPP dstance to the US and columns 5-8 use CPP dstance to 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 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, growng 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 A7: CPP Distance 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 Distance to the US			
CPP Distance (0-1)	-9.122***	-8.626***	1.555	0.457***	0.254**	0.966***	0.619***
	(1.152)	(1.168)	(1.290)	(0.133)	(0.121)	(0.241)	(0.228)
Observations	6,915	5,493	5,844	4,580	4,559	4,580	4,559
R-squared	0.600	0.531	0.648	0.243	0.262	0.661	0.667
				Panel B: CPP Distance to Estimated Frontier Set			
CPP Distance (0-1)	-6.963***	-5.325***	-0.243	0.331***	0.182*	0.594***	0.323*
	(0.934)	(0.852)	(0.856)	(0.104)	(0.102)	(0.189)	(0.187)
Observations	6,693	5,330	5,677	4,481	4,461	4,481	4,461
R-squared	0.600	0.535	0.649	0.242	0.261	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 A8: CPP Distance Effects and Innovation

	(1)	(2)
Dependent Variable:	log(BioTech Developed)	IP Protection (0/1)
β^{ℓ}	-0.578***	-0.133***
	(0.159)	(0.0173)
Observations (Countries)	59	242
R-squared	0.171	0.248

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 distance to 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 A9: 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 A10: Inappropriateness and the Efficacy of the Green Revolution

	(1)	(2)	(3)	(4)	(5)
	Pct. Modern Variety Adoption			Δ log Output	Δ log Area Harvested
CPP Dist. to Green Revolution 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 distance 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 A11: Inappropriateness and the Efficacy of 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 Dist. to 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 distance 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-perod 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 ni columns 4-7, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A12: CPP Distance Inhibits Biotechnology Adoption in Africa

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is Improved Seed Use (=1)					
	Panel A: CPP Dstance to the US					
CPP Distance (0-1)	-0.256***	-0.223***	-0.223***	-0.155***	-0.205***	-0.354***
	(0.0825)	(0.0744)	(0.0750)	(0.0522)	(0.0689)	(0.105)
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	0.248
	Panel B: CPP Distance to Estimated Frontier Set					
CPP Distance (0-1)	-0.314***	-0.249***	-0.246***	-0.154***	-0.227***	-0.246***
	(0.0821)	(0.0822)	(0.0829)	(0.0560)	(0.0793)	(0.0829)
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) Distance 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 distance to the frontier is estimated as pathogen distance to 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 distance 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.

B. Omitted Proofs and Definitions

B.1 Statement and Proof of Lemma 1

We first state and prove a result deriving the optimal planting patterns in each country.

Lemma 1. *The measure of farmers planting crop k with technology ℓ' incountry ℓ is given by*

$$\pi(k, \ell', \ell) = \frac{p(k)^\eta \theta(k, \ell' \to \ell)^\eta \omega(k, \ell)^\eta}{\sum_{k', \ell''} p(k')^\eta \theta(k', \ell'' \to \ell)^\eta \omega(k', \ell)^\eta} \tag{B.1}$$

Proof. Let $u_i^* \in \{1, \ldots, K\} \times \{1, \ldots, L\}$ denote the crop-technology choice of farmer i, let $\nu(k, \ell', \ell) = p(k)\omega(k, \ell)\theta(k, \ell' \to \ell)$ determine the shifters of revenue productivity for each (k, ℓ') pair in ℓ, and let $\pi(k, \ell', \ell) = \mathbb{P}[u_i^* = (\ell', k)]$ if $i \in [\ell - 1, \ell)$, which does not depend on the index i within a given farming country ℓ.[57] Let $F(z)$ denote the cumulative distribution function of a Fréchet random variable with scale one and shape parameter $\eta > 1$, or

$$F(z) = \exp\left(-x^\eta\right) \tag{B.2}$$

The random shock $\varepsilon_i(i, \ell')$ is Fréchet random variable with *mean* one and shape parameter $\eta > 1$, so its scale parameter is $s = (\Gamma(1 - 1/\eta))^{-1}$; thus the normalized shock $\hat{\varepsilon}_i(i, \ell') = \frac{1}{s}\varepsilon_i(i, \ell')$ is distributed by $F(z)$. If a farmer draws $\hat{\varepsilon}_i(k, \ell') = z$ for their random productivity, then that farmer chooses pair (k, ℓ') only if this results in the maximum productivity among all options, or

$$\nu(k, \ell', \ell) z > \nu(k', \ell'', \ell) \hat{\varepsilon}_i(k', \ell'') \tag{B.3}$$

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:

$$\pi(k, \ell' \to \ell) = \int_0^\infty \prod_{k', \ell'' \neq k, \ell'} F\left(\frac{\nu(k, \ell', \ell)}{\nu(k', \ell'', \ell)} z\right) \mathrm{d}F(z) \tag{B.4}$$

Substituting Equation B.2 into Equation B.4 and simplifying yields the expression

$$\pi(k, \ell', \ell) = \int_0^\infty \exp\left(-z^{-\eta} \frac{\Xi(\ell)^\eta}{\nu(k, \ell', \ell)^\eta}\right) z^{-1-\eta} \, \mathrm{d}z \tag{B.5}$$

[57] By a law of large numbers across i.i.d. realizations of the shocks, this corresponds with the measure of farmers making the specified choice.

where we define the productivity index

$$\Xi(\ell) = \left(\sum_{k=1}^{K} \sum_{\ell'=1}^{L} \nu(k, \ell', \ell)^{\eta} \right)^{\frac{1}{\eta}} \tag{B.6}$$

which corresponds with the index defined in Equation 2.6 in the main text. See that, after a change in variables in the integrand to

$$\tilde{z} = z \frac{\nu(k, \ell', \ell)}{\Phi(\ell)} \tag{B.7}$$

that the original integral can be re-written and simplified as

$$\begin{aligned} \pi(k, \ell', \ell) &= \frac{\nu(k, \ell', \ell)^{\eta}}{\sum_{k', \ell''} \nu(k', \ell'', \ell)^{\eta}} \int_0^{\infty} \exp\left(-\tilde{z}^{-\eta}\right) \tilde{z}^{-1-\eta} \, \mathrm{d}z \\ &= \frac{\nu(k, \ell', \ell)^{\eta}}{\sum_{k', \ell''} \nu(k', \ell'', \ell)^{\eta}} \int_0^{\infty} \mathrm{d}F(\tilde{z}) \\ &= \frac{\nu(k, \ell', \ell)^{\eta}}{\sum_{k', \ell''} \nu(k', \ell'', \ell)^{\eta}} \end{aligned} \tag{B.8}$$

Re-writing the last line with the definition of $\nu(k, \ell', \ell)$ completes the proof □

B.2 Proof of Proposition 1

We first derive the program of an innovator for profit-maximizing research. Fix the innovator's country ℓ' and crop k. Since individual innovators are small, the measure of farmers using any technology $j \in [\ell' - 1, \ell')$ in country ℓ for crop k is given by $\pi(k, \ell', \ell)$ as derived in Lemma 1 and Equation B.1. If all innovators have the same technology quality, or $\theta_j(k, \ell') \equiv \theta(k, \ell' \to \ell)$, then the productivity of each farmer planting (k, ℓ') is given by $\Xi(\ell)$, defined in Equation in 2.6, due to the arguments in the proof of Proposition 2. Finally, the productivity of a farmer planting technology j is given by $\Xi(\ell) \frac{\theta_j(k,\ell)}{\theta(k,\ell' \to \ell)}$, where the second term measures any differential productivity relative to the average quality of technology. The innovator chooses general research, or $A_j(k)$, and pest-specific research, or the mapping $t, \ell \mapsto B_j(t, k, \ell)$, to solve the program

$$\max_{A_j(k), B_j(t,k,\ell) > 0} \sum_{\ell=1}^{L} \rho(\ell, \ell') \pi(k, \ell', \ell) \Xi(\ell) \frac{\theta_j(t, k, \ell')}{\theta(k, \ell' \to \ell)} - \sum_{\ell=1}^{L} \int_{\mathcal{T}} C(B_j(t, k, \ell); t, k, \ell') \, \mathrm{d}t - Q(A_j(k)) \tag{B.9}$$

where $\mathcal{T}$ denotes the set of all pests and $Q(\cdot)$ denotes the cost of researching general technology, which we assume to be convex. The program is concave, owing to the concavity of the objective (which is "Cobb-Douglas," with constant returns to scale) and convexity of all costs, and its solution is characterized by necessary first-order conditions for each choice variable.

We first establish two basic observations about pest-specific research within the home country ℓ'. See that, for any k and $t \notin \mathcal{T}(k, \ell')$, there is zero marginal benefit to research. Therefore, it is

necessary in any optimal allocation for $B_j(t,k,\ell') \equiv 0$ for all k and $t \notin \mathcal{T}(k,\ell')$. Next, see that the first-order condition for any k and $t \in \mathcal{T}(k,\ell)$ is

$$(1-\alpha)\rho(\ell',\ell')\pi(k,\ell',\ell')\Xi(\ell')\frac{\theta_j(t,k,\ell')}{\theta(k,\ell'\to\ell')} = B_0 B_j(t,k,\ell')^{\phi+1}\exp(-\tau B(t,k,\ell')) \tag{B.10}$$

Under a symmetric equilibrium, this has a unique solution $B(k,\ell') > 0$ for any specific pest.

We next focus on the first-order conditions for each $B_j(t,k,\ell)$ for $\ell \neq \ell$. There are three cases. First, $t \notin \mathcal{T}(k,\ell)$ or the pest is not present, marginal benefits are zero and optimal investment is zero. Second, if $t \in \mathcal{T}(k,\ell)$ and $t \notin \mathcal{T}(k,\ell')$, then the first-order condition is given by the following

$$(1-\alpha)\rho(\ell,\ell')\pi(k,\ell',\ell)\Xi(\ell)\frac{\theta_j(t,k,\ell')}{\theta(k,\ell'\to\ell)} = B_0 B_j(t,k,\ell)^{\phi+1} \tag{B.11}$$

incorporating the zero knowledge spillover, from zero ℓ' research. Finally, if $t \in \mathcal{T}(k,\ell)$ and $t \in \mathcal{T}(k,\ell')$, then the first-order condition is given by the following that incorporates the knowledge spillover:

$$(1-\alpha)\rho(\ell,\ell')\pi(k,\ell',\ell)\Xi(\ell)\frac{\theta_j(t,k,\ell')}{\theta(k,\ell'\to\ell)} = B_0 B_j(t,k,\ell)^{\phi+1}\exp(-\tau B(k,\ell')) \tag{B.12}$$

We focus on symmetric equilibria in which $\theta_j(t,k,\ell' \equiv \theta(k,\ell'\to\ell)$ for all $j \in [\ell'-1,\ell)$ and $B(t,k,\ell')^\tau \equiv B(k,\ell')^\tau$ for all $t \in \mathcal{T}(k,\ell')$. In this case, $\frac{\theta_j(t,k,\ell')}{\theta(k,\ell'\to\ell)} = 1$ in each equation.

We now derive the the expression for technology transfer, Equation 2.4. Taking logs, integrating Equations B.11 and B.12 over all pests $t \in \mathcal{T}(k,\ell)$, and adding $\log A(k,\ell')$, we derive the following condition for $\log\theta(k,\ell'\to\ell)$:

$$\begin{aligned}\frac{1+\phi}{1-\alpha}\log\theta(k,\ell'\to\ell) = \log(1-\alpha) - \log B_0 + \log\rho(\ell,\ell') + \tau B(k,\ell') - \delta(k,\ell',\ell)\tau B(k,\ell') \\ + \log\Xi(\ell) + \log\pi(k,\ell',\ell) + \frac{\alpha}{1-\alpha}(1+\phi)\log A(k,\ell')\end{aligned} \tag{B.13}$$

Substituting in the expression for $\pi(k,\ell',\ell)$ from Lemma 1, this re-arranges as desired to

$$\log\theta(k,\ell'\to\ell) = \beta(k,\ell')\cdot\delta(k,\ell',\ell) + \chi(k,\ell) + \chi(k,\ell') + \chi(\ell,\ell') \tag{B.14}$$

with the fixed effects defined by

$$\begin{aligned}\chi(k,\ell) &= \frac{1-\alpha}{1+\phi-(1-\alpha)\eta}\left(\eta\log p(k) + \eta\log\omega(k,\ell) - (\eta-1)\Xi(\ell)\right) \\ \chi(k,\ell') &= \frac{1-\alpha}{1+\phi-(1-\alpha)\eta}\left(\tau B(k,\ell') + (1+\phi)\log A(k,\ell')\right) \\ \chi(\ell',\ell) &= \frac{(1-\alpha)(\log\rho(\ell',\ell) + \log(1-\alpha) - \log B_0)}{1+\phi-(1-\alpha)\eta}\end{aligned} \tag{B.15}$$

and coefficient

$$\beta(k, \ell') = -\frac{(1-\alpha)\tau B(k, \ell')}{1+\phi-(1-\alpha)\eta} \tag{B.16}$$

As $1+\phi-(1-\alpha)\eta > 0$, by the assumption stated in Footnote 13, we furthermore have that $\beta(k, \ell') \leq 0$.

B.3 Proof of Proposition 2

We first derive productivity of k, ℓ' production conditional on choice. Let

$$V_i^* = \max_{k', \ell''} \{\psi_i(k', \ell'')\} \tag{B.17}$$

denote the productivity 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 B.4 up to the realization $\frac{v}{s\nu(k', \ell'', \ell)^\eta}$, and normalizing by the probability of choosing (k', ℓ''):

$$\mathbb{P}[V_i^* \leq v \mid u_i^* = (k', \ell'')] = \frac{1}{\pi(k, \ell' \to \ell)} \int_0^{\frac{v}{s\nu(k', \ell'', \ell)^\eta}} F\left(\frac{\nu(k, \ell', \ell)^\eta}{\nu(k', \ell'', \ell)^\eta} z\right) \mathrm{d}F(z) \tag{B.18}$$

Doing the same manipulation of the integrand and change-of-variables as in the proof of Lemma 1, we can re-express this probability as

$$\mathbb{P}[V_i^* \leq v \mid u_i^* = (k', \ell'')] = \int_0^{\frac{v}{s\Xi(\ell)}} \mathrm{d}F(\tilde{z}) \tag{B.19}$$

which implies that V_i^*, conditional on $u_i^* = (k', \ell'')$, can be written as the product of $\Xi(\ell)$ 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 $\mathbb{E}[V_i^* | u_i^* = (k', \ell'')] = \Xi(\ell)$ for any (k', ℓ''), as well as unconditionally.

We can now prove each claim in the Proposition, starting with claim 3. The physical yield of crop k in country ℓ is, appealing to the relevant law of large numbers, equal to the expected physical production per unit area:

$$z(k, \ell) = \frac{1}{p(k)} \mathbb{E}\left[V_i^* \mid u_i^* = (k, \ell'), \ell' \in \{1, \ldots, L\}\right] \tag{B.20}$$

As established above, the conditional expectation is $\Xi(\ell)$. Taking logs yields the desired expression.

Next, for claim 2, see that by the law of large numbers the planted area equals the probability of selecting crop k with any location ℓ'. This is

$$\pi(k, \ell) = \frac{\sum_{\ell'}^{L} \nu(k, \ell', \ell)^\eta}{\sum_{k', \ell''} \nu(k', \ell'', \ell)^\eta} \tag{B.21}$$

The desired result is immediate from plugging in the definition of $\Theta(k, \ell)$, after taking logs.

Finally, see that physical production can be written as

$$Y(k, \ell) = \sum_{\ell'}^{L} \mathbb{E}\left[\frac{V_i^*}{p(k)} \mid u_i^* = (k, \ell')\right] \cdot \pi(k, \ell', \ell) \tag{B.22}$$

By the arguments above, $\mathbb{E}\left[\frac{V_i^*}{p(k)} \mid u_i^* = (k, \ell')\right] \equiv \frac{\Xi(\ell)}{p(k)}$ and hence

$$Y(k, \ell) = \frac{\Xi(\ell)\pi(k, \ell')}{p(k)} \tag{B.23}$$

proving the result.

B.4 Statement and Proof of Corollary 1

Corollary 1. *The fraction of crop k farmers using technology from country ℓ' in location ℓ is given by*

$$\log \pi(k, \ell' \to \ell) = \eta \cdot \beta(k, \ell') \cdot \delta(k, \ell', \ell) + \hat{\chi}(k, \ell) + \hat{\chi}(k, \ell') + \hat{\chi}(\ell, \ell') \tag{B.24}$$

where $\beta(k, \ell') \leq 0$ is given in Equation 2.5, and the $\hat{\chi}(\cdot)$ are additive effects varying at the indicated level.

First, see that we can write the conditional probability of using technology from ℓ' in terms of the probabilities of choosing each (k, ℓ') pair:

$$\pi(\ell' \mid k, \ell) = \frac{\pi(k, \ell', \ell)}{\sum_{\ell''=1}^{L} \pi(k, \ell'', \ell)} \tag{B.25}$$

Applying Lemma 1, and simplifying, we derive

$$\begin{aligned} \pi(\ell' \mid k, \ell) &= \frac{p(k)^{\eta}\theta(k, \ell' \to \ell)^{\eta}\omega(k, \ell')^{\eta}}{\sum_{\ell''=1}^{L} p(k)^{\eta}\theta(k, \ell'' \to \ell)^{\eta}\omega(k, \ell)^{\eta}} \\ &= \frac{\theta(k, \ell' \to \ell)^{\eta}}{\sum_{\ell''=1}^{L} \theta(k, \ell'' \to \ell)^{\eta}} \end{aligned} \tag{B.26}$$

We finally take logs to derive Equation B.24, defining the fixed effects as

$$\begin{aligned} \hat{\chi}(k, \ell) &= \eta\chi(k, \ell) - \log\left(\sum_{\ell''=1}^{L} \theta(k, \ell'' \to \ell)^{\eta}\right) \\ \hat{\chi}(k, \ell') &= \eta\chi(k, \ell') \\ \hat{\chi}(\ell', \ell) &= \eta\chi(\ell', \ell) \end{aligned} \tag{B.27}$$

where $(\chi(k, \ell), \chi(k, \ell'), \chi(\ell', \ell))$ are the same as in Equation 2.4, and as defined in the proof of Proposition 1.

B.5 Counterfactual Calculation Details

Here, we detail the three counterfactual calculations which were described in Section 7.1.

The first is a *first-order calculation*, which has the advantage of using as little as possible the model structure at the cost of missing many channels of adjustment to the productivity shock. In particular, up to an approximation around the observed allocation, counterfactual productivity at fixed prices is the following:

$$\log \overline{\Xi}(\ell)^{\text{FO}} - \log \hat{\Xi}(\ell) = -\frac{\beta}{\eta} \times \left(\sum_{k=1}^{K} \frac{\text{Area}(\ell, k)}{\sum_{k'=1}^{K} \text{Area}(\ell, k')} \times \text{CPPDistFrontier}(k, \ell) \right) \tag{B.28}$$

The term in parentheses on the right is the area-weighted sum of distance to the frontier across crops, which is also fully observable for our studied panel of countries and crops. This term is rescaled by our estimate of $\overline{B} = \beta/\eta$ ("log productivity per distance unit").

The second method traces out re-allocation across crops in response to the shock, again under the assumption of fixed prices ("FP"):[58]

$$\log \overline{\Xi}(\ell)^{\text{FP}} - \log \hat{\Xi}(\ell) = -\frac{1}{\eta} \log \left(\sum_{k=1}^{K} \frac{\text{Area}(\ell, k)}{\sum_{k'=1}^{K} \text{Area}(\ell, k')} \times \exp\left(\beta \times \text{CPPDistFrontier}(k, \ell)\right) \right) \tag{B.29}$$

A direct comparison of Equations B.28 and B.29 suggests that the latter, by modeling farmers' switching to more productive (away from less productive) crops, should exaggerate gains from positive shocks and mitigate losses from negative shocks, if those shocks have very uneven incidence across crops. The parameter η controls the elasticity of substitution for farmers growing those crops, a more demanding interpretation than its role as the crop-by-crop elasticity of supply in the First Order approach.

The final method takes into account both production re-allocation and global equilibrium adjustment via prices. This calculation is a fixed point among three equations. The first is an adjustment of revenue productivity to take into account relative price changes $\overline{p}(k)/\hat{p}(k)$:

$$\log \overline{\Xi}(\ell)^{\text{P}} - \log \overline{\Xi}(\ell)^{\text{FP}} = \frac{1}{\eta} \log \left(\sum_{k=1}^{K} \frac{\text{Area}(\ell, k)}{\sum_{k'=1}^{K} \text{Area}(\ell, k')} \times \left(\frac{\overline{p}(k)}{\hat{p}(k)} \right)^{\eta} \right) \tag{B.30}$$

The second is the expression for physical production as a function of productivity in Proposition 2 (Equation 2.7). And third is a system system of global demand curves for each crop,

$$\frac{\overline{p}(k)}{\hat{p}(k)} = \left(\frac{\overline{Y}(k)}{\hat{Y}(k)} \right)^{-\varepsilon} \tag{B.31}$$

[58] The observed area weights enter via an intermediate calibration step. To justify the observed allocation of land, we back out the local revenue productivity at the current technology and prices; these are proportional to areas raised to the power η, which then re-enter the productivity calculation.

The calibration of these demand curves is, as described in the main text, taken from estimates of Regmi and Seale (2010) for the elasticity of substitution between food and other goods. This is the right elasticity of substitution to consider for the above demand system, in which all crops are substituted against the numeraire good.

C. Additional Empirical Analysis

C.1 Invasive Species

In our baseline estimates, we construct CPP distance using all known pests and pathogens 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 conceptual question is whether the baseline findings are driven by invasive species, or persistent differences in ecology across crops and locations. Invasive species can cause disproportionate damage to plants and agricultural production since they often have fewer natural predators in the new environment, and other species have not evolved natural defense mechanisms. However, as discussed in the main text, there are several examples of persistent differences in CPP environment across locations shaping the effectiveness of technology (see Section 3.1). Moreover, 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).[59] The ISC is a list of global invasive species, as determined by extensive literature searches and trawls of existing invasive species lists. Since the ISC is also a CABI data set, we can use the unique species identifiers to like ISC species to CPC species in our main CPP data set. 748 CPPs from our main sample are listed as invasive species in the ISC, comprising about 15% of our main CPP sample. We then estimate all versions of CPP distance from the main text *after restricting the sample of CPPs to non-invasive species*, and re-produce all of our main estimates using the CPP distance measures purged of variation from invasive species.[60]

The estimates are presented in Table C1. Columns 1-3 report estimates corresponding to our analysis of international technology diffusion and columns 4 and 5 report estimates correspond to our analysis of biotechnology adoption and output respectively. Compared to our baseline estimates, the effects on technology diffusion are (if anything) slightly larger, and the effects on output are slightly smaller (although the standardized effect is similar, since the standard deviation of CPP distance without invasive species is somewhat smaller). These findings do not suggest that the baseline results are driven by invasive species.

C.2 Inappropriateness Driven By Non-CPP Agro-Climatic Conditions

C.2.1 Constructing Agro-climatic Distance

We include ten key agroclimatic characteristics that shape the usefulness of biotechnology for production in a region: temperature, precipitation, elevation, ruggedness, the growing season, and soil

[59] The ISC homepage can be found here: https://www.cabi.org/isc

[60] It could be ideal to only exclude country-CPP pairs where the CPP is known to by invasive. However, we are unaware of systematic data on the locations of species invasion; CABI do not report this level of detail.

Table C1: CPP Distance Without Invasive Species: All Estimates

	(1)	(2)	(3)	(4)	(5)
	Technology Trasnfer			Technology Adoption	Output
Dependent Variable:	asinh Biotech Transfer	Any Biotech Transfer	log Biotech Transfer	Improved Seed (=1)	log Output
CPP Distance Without Invasive Species	-0.0712***	-0.0304***	-0.5451		
	(0.0241)	(0.0096)	(0.34)		
CPP Distance to Frontier Without Invasive Species				-0.248***	-6.335***
				(0.0743)	(0.948)
Crop-by-Origin Fixed Effects	Yes	Yes	Yes	-	-
Crop-by-Destination Fixed Effects	Yes	Yes	Yes	-	-
Country Pair Fixed Effects	Yes	Yes	Yes	-	-
Country Fixed Effects	-	-	-	Yes	Yes
Crop Fixed Effects	-	-	-	Yes	Yes
Observations	202,154	202,154	5,752	115,397	6,858
R-squared	0.4397	0.3831	0.7965	0.213	0.584

Notes: The unit of observation is a crop-origin-destination in columns 1-3 and a crop-country pair in columns 4-6. Standard errors are double-clustered by origin and destination in columns 1-3, clustered y crop-country in columns 4-5, and double clustered by crop and country in column 6. CPP Distance to Frontier is computed as agroclimatic distance to the US. 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.

acidity, clay content, silt content, coarse fragment content, and water capacity.[61] We combine geographically coded raster files of each aforementioned characteristic with grid-cell level information from the EarthStat database, which reports the global planting pattern of 175 important crops in the year 2000 (Monfreda et al., 2008).[62] 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 just the land that EarthStat identifies is devoted to the crop in question*; we denote these as $x_{k,\ell}$. We then simply normalize each characteristic so that all are in comparable 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 $\hat{x}_{k,\ell}$. For each agro-climatic characteristic $x \in \mathcal{X}$ we define:

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

where, in words, $\hat{x}_{k,\ell,\ell'}$ is the normalized distance ("inappropriateness") in agro-climatic feature x for crop k between countries ℓ and ℓ'. For simplicity, we also aggregate the individual agroclimatic

[61] This set of characteristics builds from earlier work on the transferability of agricultural knowledge across ecologically different regions (see, for example, Bazzi et al., 2016).

[62] The data set is described and can be accessed here: http://www.earthstat.org/harvested-area-yield-175-crops/. The data set was created by combining national, state, and county level census data with information on crop-specific maximum potential yield around the world, to construct a 5-minute by 5-minute grid of the area devoted to each of 175 important crops circa the year 2000.

characteristics into a single index at the crop-by-country-pair level:

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

where $\mathcal{X}$ is the set of agro-climatic characteristics x. The index is similar to the agro-climatic similarity index used by Bazzi et al. (2016) to study patterns of migration. This index has the attractive feature that it is additively separable the x's and therefore simple to separate the contribution of each attribute.

C.2.2 Empirical Estimates

We next investigate the role of differences across agro-climatic features in shaping the transfer of technology and productivity differences. Column 1 of Table C2 re-produces our baseline estimate of Equation 4.1 on the sample of country-pairs and crops for which all agro-climatic features could be measured. Our estimate is negative, significant, and slightly larger in magnitude than our estimate on the largest possible sample reported in the main text. In column 2, we add $\Delta x_{k,\ell,\ell'}$ for all $x \in \mathcal{X}$. Consistent with agricultural biotechnology also being specific to particular non-CPP features of the environment (e.g. via repeated selection in a particular local environment), the coefficients on the $\Delta x_{k,\ell,\ell'}$ are almost all negative and some are statistically significant. Differences in temperature and precipitation are associated with the largest reductions in technology transfer, and there is also a significant effect of differences in elevation and soil pH. Despite the inclusion of all these additional distance metrics, however, the coefficient on CPP distance barely changes. In column 3, we include the one-dimensional $\text{AgroClimDist}_{k,\ell,\ell'}$ on the right hand side of the regression in place of the individual characteristics. The coefficient on agro-climatic distance is negative and significant; however, the coefficient on CPP distance again remains very similar.

Table C3 is structured like Table C2, except the dependent variable is log of agricultural output and the regression specification is Equation 5.2. While differences in non-CPP agro-climatic features compared to technology producing countries intuitively lower output, these effects again operate largely independently from CPP distance. Taken together, these findings 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 as we measure them seem to operate independently from our baseline measure of CPP distance, 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 distance to the frontier, and distance to the frontier in each other ecological characteristic, is relatively low. Table C4 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

Table C2: Agro-climatic Differences and Technology Transfer

	(1)	(2)	(3)
	Dependent Variable is (asinh) Biotechnology Transfers		
CPP Distance (0-1)	-0.0766**	-0.0722**	-0.0737**
	(0.0318)	(0.0312)	(0.0314)
Distance in:			
Temperature		-0.0107*	
		(0.00619)	
Precipitation		-0.0141*	
		(0.00805)	
Elevation		-0.00590*	
		(0.00311)	
Ruggedness		-0.000643	
		(0.00245)	
Soil Clay Content		-0.00597	
		(0.00568)	
Soil Silt Content		0.00340	
		(0.00574)	
Soil Coarse Fragment Content		0.000886	
		(0.00318)	
Soil pH		-0.00825**	
		(0.00355)	
Growing Season Length		-0.00453	
		(0.00519)	
Available Water Capacity		-0.00561	
		(0.00466)	
Agro-Climatic Index			-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. Distance 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 C3: Agro-climatic Differences and Agricultural Output

	(1)	(2)	(3)
	Dependent Variable is log Output		
CPP Distance (0-1)	-9.884***	-8.727***	-9.119***
	(1.467)	(1.359)	(1.441)
Distance in:			
Temperature		-0.568***	
		(0.154)	
Precipitation		-0.329*	
		(0.186)	
Elevation		0.146	
		(0.0921)	
Ruggedness		-0.248*	
		(0.135)	
Soil Clay Content		0.0680	
		(0.0973)	
Soil Silt Content		0.0202	
		(0.122)	
Soil Coarse Fragment Content		-0.325**	
		(0.133)	
Soil pH		-0.0694	
		(0.107)	
Growing Season Length		0.0819	
		(0.125)	
Available Water Capacity		-0.260**	
		(0.116)	
Agro-Climatic Index			-1.294***
			(0.281)
p-value joint significance	-	0.000	-
Crop Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Observations	5,285	5,270	5,285
R-squared	0.576	0.591	0.583

Notes: The unit of observation is a crop-country pair. Distance 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 crop and country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table C4: Correlation Matrix: All Ecological Distance 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 frontienr, 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.

all other distance measures; the correlation coefficients tend to be small, and only one is above 0.2. Several are 0.1 or below. The remainder of the table includes correlation coefficients among all other pairs of ecological characteristics.

Finally, Table C5 reproduces all baseline estimates from the main paper, using $\text{AgroClimDist}_{k,\ell,\ell'}$ as our shifter of inappropriateness in place of CPP distance. Across dependent variables, the results are qualitatively very similar; the one exception is that we find no effect of agro-climatic distance on improved seed use in the LSMS-ISA data, while we do still find a negative effect on biocide use. Moreover, across dependent variables, these estimates imply that agro-climatic differences as we measure them have a smaller effect than CPP differences. For example, the estimate in column 6 implies, using the first order approach from the main text, that the impact of agro-climatic differences on global output are about one third the size of CPP differences.

C.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 two reasons we expect this bias to exist, which were both implicit throughout the examples given so far. 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 may take the general form of accumulated expertise, and the more specific forms (in our application) of available test fields for breeding and 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.

We explore both of these hypotheses in reduced form within our global varieties data, focusing on novel plant varieties released anywhere in the world in the 21st century. Let BioTech_k be the count

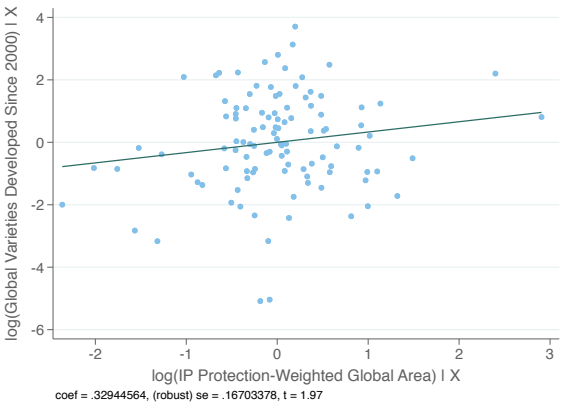
Table C5: AgroClimatic Distance and Inappropriate Technology: All Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Technology Trasnfer			Technology Adoption		Output
Dependent Variable:	asinh Biotech Transfer	Any Biotech Transfer	log Biotech Transfer	Improved Seed (=1)	Num. Biocides (0-3)	log Output
AgroClimDist	-0.0419***	-0.0171***	-0.405**			
	(0.0129)	(0.00453)	(0.189)			
AgroClimDistFrontier				0.00687	-0.484***	-1.573***
				(0.0111)	(0.169)	(0.309)
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	Yes
Crop Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	153,798	153,798	5,610	108,536	13,923	6,164
R-squared	0.440	0.387	0.779	0.219	0.260	0.558

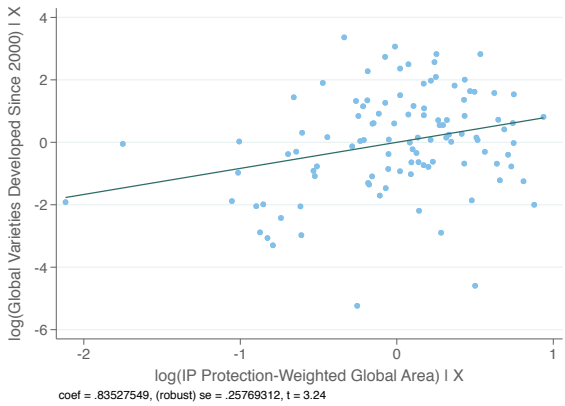
Notes: The unit of observation is a crop-origin-destination in columns 1-3 and a crop-country pair in columns 4-6. Standard errors are double-clustered by origin and destination in columns 1-3, clustered y crop-country in columns 4-5, and double clustered by crop and country in column 6. AgroClimDistFrontier is computed as agroclimatic distance to the US. 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.

Figure C1: 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 (C.3). Both are estimated from the same regression, which also included a control for log of global planted area.

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, measured in this simple way, we estimate the following regression model:

$$\ln(\text{BioTech}_k) = \alpha + \delta_1 \cdot \ln\text{WorldArea}_k + \delta_2 \cdot \ln\text{GDPArea}_k + \delta_3 \cdot \ln\text{IPArea}_k + \varepsilon_k \tag{C.3}$$

in which $\ln\text{WorldArea}_k$ is the (log of) global area devoted to crop k, and the other two regressors are espectively this area weighted by per-capita GDP (averaged over 1990-1999) and the presence of intellectual property for plant varieties as of 2000:[63]

$$\ln\text{GDPArea}_k = \ln\Big(\sum_\ell \text{Area}_{k,\ell} \cdot \text{GDP}_\ell\Big) \qquad \ln\text{IPArea}_k = \ln\Big(\sum_\ell \text{Area}_{k,\ell} \cdot \mathbb{I}_\ell^{IP}\Big) \tag{C.4}$$

We think of the first regressor, and its coefficient δ_1, as (to first approximation) a proxy for each crops 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 either channel described above.

Figure C1 reports our estimates of δ_2 and δ_3, in the form of partial correlation plots in which each dot is a crop. 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 regression 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 *does* protect intellectual property, 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 intellectual property, there would be essentially no effect.

To offer reduced-form clues that can distinguish between the two possible causes of this bias described above, we also estimate the following model at the level of crop-k and country-ℓ pairs:

$$\ln(\text{BioTech}_{k,\ell}) = \delta_0 \cdot \ln\text{Area}_{k,\ell} + \delta_1 \cdot \ln\text{WorldArea}_k + \delta_2 \cdot \ln\text{GDPArea}_k + \delta_3 \cdot \ln\text{IPArea}_k + \chi_\ell + \varepsilon_{k,\ell} \tag{C.5}$$

in which $\text{BioTech}_{k,\ell}$ is the number of varieties of crop k developed in country ℓ since 2000; and χ_ℓ are country fixed effects. The term $\delta_0 \cdot \ln\text{Area}_{k,\ell}$ 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 Equation (C.5) are reported in Table C6. We find that $\delta_0 \gg 0$, suggesting that the home market effect is an important mechanism; δ_2 and δ_3 are also positive, although only marginally significant. Finally, in this framework, $\delta_1 = 0$; un-weighted global market size is uncorrelated with technology development.

Together, this evidence suggests that in our data, technology development is biased toward the

[63] We compile the latter data using UPOV's collation of relevant intellectual property law across its member states, under the premise that participation in UPOV is essentially universal conditional on having meaningful IP protection.

Table C6: 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.

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 facts motivate our focus on the global diffusion of (in-) appropriate technology.

C.4 Technology Transfer to Africa

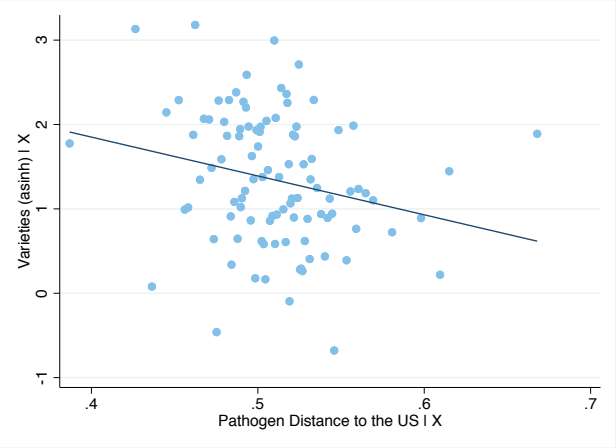
The UPOV data set tracks all plant variety certificates and as a result only covers countries for which intellectual property protection is in place; this results, as can be seen in Figure A2, several omissions, most notably much of Africa. To partially fill this gap, especially because our subsequent analysis on technology adoption focuses on sub-Saharan Africa, 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.

Empirical Estimates. 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 transfer to Africa, we estimate a simplified version of (4.1):

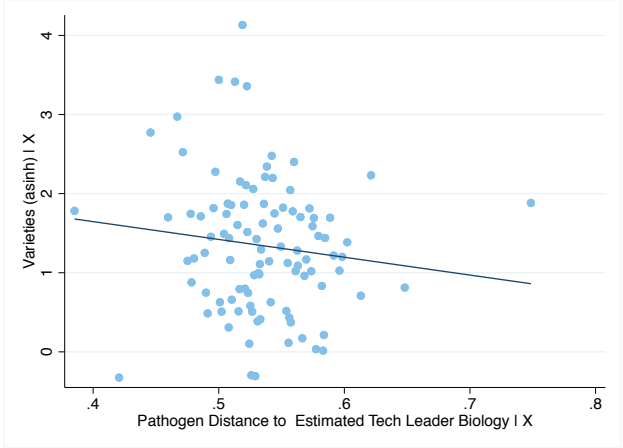
$$y_{k,\ell} = \beta \cdot \text{CPPDistFrontier}_{k,\ell} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \tag{C.6}$$

Figure C2: Pathogen Distance and Biotechnology Transfer to sub-Saharan Africa

(a) CPPDist to the US: $\beta = -4.04$ (1.09), t-stat = 3.67



(b) CPPDist to Est. Frontier: $\beta = -2.87$ (0.81), t-stat = 3.54



Notes: This figure displays binned partial correlation plots, after absorbing country and crop fixed effects, of our estimates of Equation (C.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.

where $\text{CPPDistFrontier}_{k,\ell}$ is defined using either method described in Section 5.1.2. We expect pathogen dissimilarity to the frontier to inhibit biotechnology transfer; that is, we hypothesize that $\beta < 0$. Our estimates of Equation C.6 are displayed in Figure C2. Consistent with our main technology transfer results estimated at the country pair-by-crop level, we find that pathogen distance to frontier countries significantly inhibits biotechnology introduction in sub-Saharan Africa.

C.5 Growth of US Biotechnology

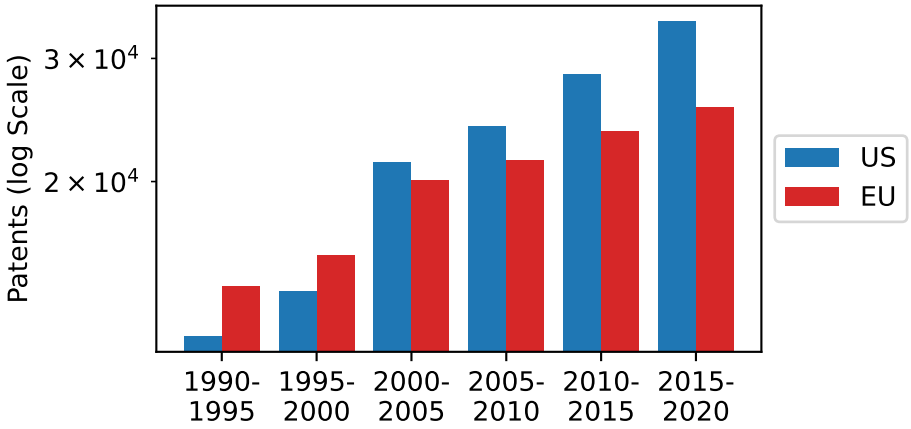
Since the 1990s, the US agricultural biotechnology sector has produced a growing share of global innovation, likely driven by the advent and increased use of genetic modification. Figure C3 displays the relative growth of US patenting since 1990; the same trend for the EU is also reported, and does not 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 (or area harvested) between the decade of the 1990s and the decade of the 2010s, and estimate:

$$\Delta \log y_{k,\ell}^{90-10} = \beta_1 \cdot \text{CPPDistance}_{k,\ell}^{US} + \beta_2 \cdot \text{CPPDistance}_{k,\ell}^{EU} + \gamma \cdot \log y_{k,\ell}^{1990} + \chi_\ell + \chi_k + \varepsilon_{k,\ell} \tag{C.7}$$

Our first hypothesis is that $\beta_1 < 0$, capturing the effect of the rise of the US on production in places

Figure C3: 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 European Union (as of 2018). Bars are the number of patents issued in the five year bin noted on the horizontal axis.

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 distance to the US to be a more important determinant of productivity changes than CPP distance to Europe.

Estimates of (C.7) are reported in Table C7, and across specifications we find evidence of both hypotheses. Dovetailing with Section 6.1, these findings convey that global productivity differences are endogenous to the evolving landscape of technology development. As a result, geography does not have a fixed impact on development, but changing effects that can be shaped by the focus and direction of innovation.

Table C7: Growth of US Biotechnology and Global Production

	(1)	(2)	(3)	(4)
	Δ log Output		Δ log Area Harvested	
CPP Distance to the US	-0.999*	-0.974*	-1.004**	-1.044*
	(0.520)	(0.572)	(0.502)	(0.533)
CPP Distance to 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 distance to the US and CPP distance to 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.