Does Technological Innovation Mitigate Agricultural Damage from Climate Change?

Jack Fitzgerald*

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Abstract

Moscona & Sastry (2023, *Quarterly Journal of Economics*) – henceforth MS23 – find that cropland values are significantly less damaged by extreme heat exposure (EHE) when crops are more exposed to technological innovation. However, MS23's 'innovation exposure' variable does not directly measure innovation, instead proxying innovation based on crops' national EHE. A critical re-examination of MS23's replication data shows that this proxy will moderate EHE impacts for reasons unrelated to innovation. Specifically, the proxy is practically indistinguishable from local EHE, so MS23's models examining interaction effects between their proxy and local EHE are effectively interacting local EHE with itself. Resultantly, I show that modelling agricultural land values as a second-order polynomial of local EHE produces qualitative conclusions that are nearly identical to those obtained by MS23. I then construct direct measures of innovation exposure from MS23's crop variety and patenting data. Replacing MS23's proxy with these direct measures of innovation decreases MS23's moderating effect estimates by at least 99.8% in standardized units; none of these new estimates are statistically significantly different from zero. These results cast doubt on MS23's aggregate projections of historical and future climate change damage mitigation from innovation, and on the general capacity for market innovations to mitigate agricultural damage from climate change. JEL Codes: O31, Q10, Q54.

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1 Introduction

As global actors determine the best course of action to address the ongoing climate crisis, there is still significant uncertainty about the level of investment that such actors should dedicate towards mitigating climate change. Based on available mitigation pathways proposed by the Intergovernmental Panel on Climate Change, global climate change mitigation costs could range from 1-7% of global GDP each year (Fujimori et al. 2023). Considerable time and effort has been invested in providing governments and businesses with estimates on the optimal location of this investment spectrum on which to fall (see Auffhammer 2018). This will depend not just on the overall costs of climate change, but also on the mitigatory impacts of adaptations in practices and technology. Substantial research has focused on the mitigatory impacts of such adaptations (e.g., see Hornbeck 2012; Carter et al. 2018; Cui 2020; Aragón, Oteiza, & Rud 2021; Lai et al. 2022; Wang et al. 2024).

Moscona & Sastry (2023) – henceforth MS23 – offer a contribution to this literature. Using data on crops and American croplands from 1950-2020, MS23 use panel data estimates to offer evidence in support of two findings. First, agricultural markets endogenously innovate to adapt to climate change: crops whose croplands are more exposed to extreme heat see increased development of crop varieties and increases in climate change-related patenting. Second, MS23 find that this innovation mitigates agricultural damage induced by climate change. MS23 construct a measure of 'innovation exposure' and estimate simple heterogeneous treatment effect (HTE) models that interact 'innovation exposure' with extreme heat exposure (EHE). These HTE models yield negative coefficients for EHE, but positive coefficients for the interaction term between 'innovation exposure' and EHE, implying that agricultural land (AL) in counties that are more exposed to innovation are less severely devalued by EHE. In fact, MS23 find that for sufficiently high 'innovation exposure', the marginal impact of EHE on AL values is not statistically significantly different from zero.

This paper critically re-examines MS23's second set of findings due to a key flaw: MS23's 'innovation exposure' measure does not directly measure innovation. Using their first set of findings as justification, MS23 instead proxy county i's 'innovation exposure' at time t using the average EHE experienced by *other counties* at time t. MS23's 'innovation exposure' proxy is thus a measure of heat, rather than innovation. Analyzing MS23's replication data (Moscona & Sastry 2022), I show that MS23's proxy is nearly indistinguishable from local EHE. This is intuitive, as both local and 'leave-one-out' EHE reflect, and are driven by, national and global climate trends.

This means that the positive coefficient on the interaction term in MS23's HTE model does not reflect mitigatory impacts of innovation on EHE-induced AL devaluation. Rather, this positive interaction effect estimate reflects the fact that the negative marginal AL devaluation impacts of *additional* increases in local EHE diminish if counties are *already* exposed to higher levels of extreme heat. This is again intuitive; though increases in EHE cause steep declines in agricultural productivity near thresholds for optimal crop-growing temperatures, if a county's heat has become so extreme that no crops can grow anyways, then additional increases in EHE will have little to no impact on AL values. I show that this nonlinearity is the effect reflected by MS23's interaction effect estimates, confirming that estimates from a specification that simply models AL values as a second-order polynomial of local EHE yield qualitative conclusions that are nearly identical to those yielded by MS23's HTE models.

This proxy is unnecessary, as MS23 have data on direct measures of innovation. MS23 obtain their first set of findings using direct data on crop variety development and climate change-related patenting. I thus use MS23's replication data to construct direct measures of innovation exposure, specifically variety exposure and patent exposure.

I then re-estimate MS23's HTE models, replacing MS23's proxy with these direct measures of innovation, and find no moderating effect estimate that is statistically significantly different from zero. The effect sizes of the moderating effect estimates in my replications are microscopic compared to MS23's estimates; the standardized coefficients of my moderating effect estimates are at least 99.8% less than the standardized coefficients of MS23's moderating effect estimates. These findings further imply that MS23's projections of historical and future damage mitigation from climate change are grossly overstated, as these projections are entirely based on MS23's HTE models. My replication thus ultimately casts doubt on the capacity of market innovations to mitigate agricultural damage induced by climate change.

Section 2 of this paper overviews MS23's replication repository, published estimates of interest, and the reproducibility of such estimates. Section 3 then details MS23's proxy, as well as its inappropriateness as a measure of innovation for the purposes of MS23's estimations of interest. Thereafter, Section 4 introduces the two direct innovation measures I construct from MS23's replication data. Section 5 displays the results after re-estimating MS23's HTE models using my direct innovation measures, and Section 6 concludes.

2 Data, Published Findings, and Reproducibility

My analyses rely on MS23's replication repository (Moscona & Sastry 2022). Appendix Table A-I details the completeness of the repository, with specific regard to its completeness for producing Table III and Figure VI. Raw data appears to be fully available. However, there does not appear to be sufficient cleaning code to convert the raw data into cleaned datasets. Specifically, no instructions are provided in the repository's ReadMe file for reproducing dataset `county_level_data.dta`. This file – the analysis data for the replications of interest – is made available in the replication repository. However, the repository's analysis code contains minor errors. I thus classify the results as partially reproducible, and discuss these coding errors later in this section.

2.1 Table III

The replication of interest concerns the mitigatory effects of technological market innovations on EHE-induced AL devaluation. Let i index the county and t index the decade. By Equation 18, MS23's relevant estimates for the damage mitigation effects of technological innovation in Table III arise from a simple HTE model of the form

$$\begin{aligned}\log(\text{AgrLandPrice}_{i,t}) = {} & \delta_i + \alpha_{s(i),t} + \beta \text{ExtremeExposure}_{i,t} \\ & + \gamma \text{InnovationExposure}_{i,t} \\ & + \phi \left(\text{ExtremeExposure}_{i,t} \times \text{InnovationExposure}_{i,t}\right) \\ & + \Gamma X'_{i,t} + \epsilon_{i,t},\end{aligned} \tag{E1}$$

where $\log(\text{AgrLandPrice}_{i,t})$ represents logarithmic AL prices per cultivated land acre, δ_i are county fixed effects, $\alpha_{s(i),t}$ are state-by-year fixed effects, and $X'_{i,t}$ is a matrix of control covariates. I defer discussion of $\text{ExtremeExposure}_{i,t}$ and $\text{InnovationExposure}_{i,t}$ to Section 3.

The model in Equation E1 is estimated using a county-decade panel dataset with $t \in \{1950, 1960, \cdots 2010\}$. To provide an example of indexing, $t = 1950$ implies that the observation covers all years between 1950-1959, inclusive of endpoints. Table III is estimated using two types of specifications. Models 1-5 are estimated using a *'long-difference' (LD)* specification, which restricts time periods to $t \in \{1950, 2010\}$. Models 6-7 are estimated using a panel specification with no such temporal restrictions.

[Table R–I about here]

ϕ is the parameter of interest for MS23's findings concerning the mitigatory impact of technological innovation on climate change damage. Table R–I shows $\hat{\beta}$ and $\hat{\phi}$ estimates, with standard errors (SEs) double-clustered at the county and state-decade levels.[1] Panel A directly copies the published results from MS23, and Panel B shows the results from my reproduction, confirming that the replication repository permits a nearly exact reproduction of Table III. The only differences between my reproductions and the published estimates in Table III are the observation counts in Models 6 and 7; MS23 report 0.2% fewer observations than I obtain in my computational reproductions. MS23 obtain significantly positive estimates for ϕ, and interpret this to mean that croplands which are more exposed to innovation experience less devaluation when exposed to extreme heat.

To provide a sense of scale for these estimates, Panels C-D of Table R–I convert the $\hat{\phi}$ and $\hat{\beta}$ estimates from Table III into two standardized effect size measures. Panel C converts the estimates into partial correlation coefficients r, and subsequently into SE(r), using the following representation (van Aert & Goos 2023):

$$r = \frac{t}{\sqrt{t^2 + df}} \qquad\qquad \text{SE}(r) = \frac{1 - r^2}{\sqrt{df}}, \tag{E2}$$

where t is the usual t-statistic and df is the model's residual degrees of freedom. The partial correlation coefficients of $\hat{\phi}$ in my reproduction of Table III range from 0.156 to 0.505. Partial

[1] I focus on SEs double-clustered at the county and state-decade levels rather than SEs clustered solely at the state-decade level for two reasons. First, double clustering appears to produce smaller SEs for most of MS23's models. Second, 'treatment status' – in this case EHE/innovation exposure – is more credibly assigned at the county level than at the state-decade level.

correlations of this magnitude range from small to large amongst published effect sizes in economics (Doucouliagos 2011).

Panel D converts the estimates into standardized coefficients σ. Let D be a given independent variable (either EHE or its interaction with innovation exposure) and Y be the dependent variable (logarithmic AL value). Because all D and Y are continuous, I compute σ and SE(σ) using estimate $\hat{\tau} \in \left\{\hat{\phi}, \hat{\beta}\right\}$ via the formulas

$$\sigma = \frac{\hat{\tau}\sigma_D}{\sigma_Y} \qquad \mathrm{SE}(\sigma) = \frac{\mathrm{SE}\left(\hat{\tau}\right)\sigma_D}{\sigma_Y}, \tag{E3}$$

where σ_D and σ_Y respectively represent the within-sample standard deviations of D and Y.[2] σ ranges from 0.274 to 1.028 in Table R–I, ranging from small to large in standardized effect size terms (see Cohen 1988).

2.2 Figure VI

[Figure R-I about here]

MS23's Figure VI visualizes the marginal impact of county-level EHE on AL values across selected quantiles of InnovationExposure$_{i,t}$. I reproduce Figure VI, along with two corrections thereof, in Figure R-I. The left graph in Figure R-I reproduces Figure VI based on MS23's replication code, though like the middle and right graphs, the y-axis of this graph is given a custom scale to ensure uniform y-axis scaling across all three graphs.

I detect a minor error in MS23's construction of Figure VI: the values used to construct the quantiles are incorrectly hard-coded into the do-file. Specifically, in `county_level.do`, MS23 extrapolate marginal effects using Stata's `lincom` command, multiplying coefficient estimates by hard-coded numbers intended to represent the 10th, 25th, 50th, 75th, and 90th percentiles of InnovationExposure$_{i,t}$. However, these hard-coded numbers are incorrect.

The middle and right graphs in Figure R-I present extrapolated treatment effects after quantiles are corrected in one of two ways. The middle graph arises from corrected quantiles of InnovationExposure$_{i,t}$ based on the full data sample, whereas the right graph arises from

[2] Computationally, this is done by re-running the regressions of interest after dividing Y by σ_Y and each D of interest by its respective σ_D.

corrected quantiles of $\text{InnovationExposure}_{i,t}$ based only on observations from 1950 and 2010 (i.e., those in the LD specification). This correction is quite minor; the same conclusions arise for all three graphs, and the published version looks very similar to the right hand graph.

All three graphs in Figure R-I show that the marginal impact of EHE on logarithmic AL values is significantly negative for most of the distribution of $\text{InnovationExposure}_{i,t}$. However, this negative effect diminishes as $\text{InnovationExposure}_{i,t}$ increases. For sufficiently high quantiles of $\text{InnovationExposure}_{i,t}$, the impact of EHE on logarithmic AL values is not statistically significantly different from zero.

3 The Innovation Exposure Proxy

Let k index a given crop. Per Equation 8, MS23 measure EHE as $\text{ExtremeExposure}_{i,k,t}$, which is the number of degree days in county i above crop k's maximum optimal temperature in decade t. By Equation 16, MS23 measure EHE at the county level as a weighted average of $\text{ExtremeExposure}_{i,k,t}$ across all crops planted in county i, where weights are determined by the proportion of land area in county i dedicated to planting crop k at baseline:

$$\text{ExtremeExposure}_{i,t} = \sum_k \left[\frac{\text{ExtremeExposure}_{i,k,t} \times \text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \right]. \tag{E4}$$

By Equation 17, MS23 measure 'innovation exposure' as an area-weighted average across counties in a given decade, in an analagous fashion to $\text{ExtremeExposure}_{i,t}$. However, rather than an area-weighted average of $\text{ExtremeExposure}_{i,k,t}$, MS23 specify $\text{InnovationExposure}_{i,t}$ as an area-weighted average of other counties' EHE:

$$\begin{aligned}\text{InnovationExposure}_{i,t} = \sum_k & \left[\frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \right. \\ & \left. \times \sum_{j \neq i} \left[\frac{\text{Area}_{j,k}^{\text{Pre}}}{\sum_{j \neq i} \text{Area}_{j,k}^{\text{Pre}}} \times \text{ExtremeExposure}_{j,k,t} \right] \right].\end{aligned} \tag{E5}$$

Though MS23 are transparent about the calculation of $\text{InnovationExposure}_{i,t}$ in the paper, this variable does not measure innovation; it measures heat. As MS23 write (pgs. 678-

679): "[We] calculate each county's innovation exposure as the average across all crops' national extreme-heat exposure... weighted by planted areas... We make only the small change of calculating this variable leaving out the county i to avoid any mechanical correlation." In fact, MS23 primarily refer to this variable as *'leave-one-out' (LOO)* heat exposure in their replication repository.[3] I adopt this terminology to refer to MS23's innovation exposure proxy for the remainder of this paper.

This context completely changes the interpretation of ϕ in Equation E1. MS23 interpret the positive $\hat{\phi}$ estimates as evidence that the marginal AL devaluation impacts of EHE are smaller in counties whose croplands are more exposed to innovation. However, what the positive $\hat{\phi}$ estimates most directly capture is that the marginal land devaluation impacts of *local* extreme heat shocks are smaller when croplands have already experienced large *nationwide* extreme heat shocks.

[Figure R-II about here]

As a result, $\hat{\phi}$ will be positive for reasons that have nothing to do with the damage mitigation impacts of directed innovation. Specifically, $\hat{\phi}$ most likely reflects a nonlinear relationship between temperature and crop yields. Figure R-II displays the relationship that $\hat{\phi}$ is most likely capturing in Table III. In particular, Figure R-II presents a binscatter regression plot between county-level EHE and logarithmic AL value. Each bar represents a quantile bin of the distribution of $\text{ExtremeExposure}_{i,t}$, so x-axis regions with more (fewer) bars are more dense (sparse) in $\text{ExtremeExposure}_{i,t}$. The figure makes clearly visible that although local EHE decreases AL value across most of the distribution of $\text{ExtremeExposure}_{i,t}$, this relationship diminishes on average as local EHE increases, and functionally flatlines for sufficiently high values of $\text{ExtremeExposure}_{i,t}$. Because LOO EHE very closely tracks county-level EHE (see Section 3.1), the interaction term in Equation E1 is effectively interacting $\text{ExtremeExposure}_{i,t}$ with *itself*, and thus Equation E1 functionally estimates logarithmic AL values as a function of a second-order polynomial in local EHE. ϕ's sign is thus effectively the sign of the average second derivative over the function displayed in Figure R-II, and therefore, MS23's positive $\hat{\phi}$ estimates simply reflect the deceleration of negative marginal

[3] See the ReadMe files in Moscona & Sastry (2022).

EHE impacts as $\text{ExtremeExposure}_{i,t}$ increases towards the upper tail of its distribution.

Such nonlinear dynamics between temperature and AL value have been established in prior literature. For example, Schlenker & Roberts (2008; 2009) find that near maximum thresholds for optimal crop-growing temperatures, increases in temperature lead to steep declines in crop yields. However, when temperatures increase to sufficiently extreme highs, croplands can lose nearly all capacity for crop growth, so the marginal damages of additional temperature increases to crop yields diminish or even flatline. In fact, the nonlinear relationship between county-level EHE and AL values displayed in Figure R-II is fairly similar to the nonlinear relationships between temperatures and crop yields that Schlenker & Roberts (2008; 2009) find for corn, soybeans, and cotton.

This context also explains the findings in Figure VI. As national EHE grows, the marginal damages induced by local extreme heat shocks diminish, and for sufficiently high quantiles of national EHE, the marginal harms of local extreme heat shocks disappear. This is intuitive: to provide an extreme example, if nationwide extreme heat shocks have made a county's temperatures so hot that the county's croplands are completely unsuitable for agriculture, then additional local increases in temperature beyond the national extreme heat shock will have virtually zero impact on such croplands' AL value. However, this intuitive moderating relationship has nothing to do with innovation.

I show that MS23's results are an artefact of *effectively* fitting a second-order polynomial in EHE by *explicitly* fitting a second-order polynomial in EHE. Specifically, I produce specifications akin to Equation E1, but replacing the interaction specification between $\text{ExtremeExposure}_{i,t}$ and LOO EHE with a second-order polynomial in $\text{ExtremeExposure}_{i,t}$:

$$\begin{aligned}\log(\text{AgrLandPrice})_{i,t} = \delta_i + \alpha_{s(i),t} + \theta_1 \text{ExtremeExposure}_{i,t} \\ + \theta_2 \text{ExtremeExposure}^2_{i,t} + \Gamma X'_{i,t} + \epsilon_{i,t}.\end{aligned} \tag{E6}$$

In this specification, θ_1 and θ_2 are respectively akin to β and ϕ in Equation E1.

[Table R–II about here]

Table R–II displays the results from this second-order polynomial specification, which shows that fitting a second-order polynomial in county-level EHE yields results that are, qualitatively, nearly identical to MS23's results in Table III. Though Panels B-C in Table R–II show that the effect sizes of these estimates are smaller than those from Table III (see Panels C-D in Table R–I), all seven models in Table R–II yield $\hat{\theta}_1$ and $\hat{\theta}_2$ estimates that respectively hold the same signs as the $\hat{\beta}$ and $\hat{\phi}$ estimates in Table III. These $\hat{\theta}_1$ and $\hat{\theta}_2$ estimates additionally yield the same statistical significance conclusions as the $\hat{\beta}$ and $\hat{\phi}$ estimates in Table III for six of seven models.

3.1 Justifications for the Proxy

MS23 justify their innovation exposure proxy on two grounds. First, MS23 note that their earlier estimates in Section IV provide evidence that EHE is a good predictor of innovation, particularly showing that crops whose croplands are more exposed to extreme heat are also more exposed to increased innovation in crop varieties and climate change-related patenting.[4] However, this means that a proxy is unnecessary, as LD and/or panel data is available on these variables, and thus the estimation in Equation E1 can be conducted with direct measures of innovation exposure. I revisit this point in further detail in Section 4.

Second, MS23 posit that computing national EHE in LOO fashion "[purges] the measure of national crop-level damage driven by the county in question" (pg. 679). However, LOO computation does virtually nothing to rid MS23's proxy of correlations with county-level extreme heat shocks. The reason why is intuitive: both county-level and LOO EHE are driven by national-level extreme heat increases induced by global climate change. Local deviations from national climate trends are relatively small, so LOO EHE and county-level EHE are extremely similar measures.

[Figure R-III about here]

There is strong empirical evidence that MS23's LOO EHE measure closely proxies county-level EHE. Figure R-III plots the results of a binscatter regression between $\text{ExtremeExposure}_{i,t}$ and LOO heat exposure, showing that the two measures positively move together in lockstep for the vast majority of their distributions. The slope of this relationship maps very closely

[4]From MS23, pg. 679: "This measure will allow us to investigate the role of endogenous technological progress because, as documented in the first part of the article, it is a strong predictor of innovation and hence the existence of new, climate-induced technology that can be used for production in county i."

onto a 45-degree line, which would indicate a perfect one-to-one unit relationship between county-level and LOO EHEs.

Appendix Table A-II provides additional evidence showing that the two EHE measures are effectively indistinguishable. A simple random effects panel data regression of county-level EHE on LOO EHE yields a coefficient of 0.994 (SE = 0.018), implying that on average, the two measures linearly map onto one another in nearly one-to-one fashion. Marginal effect post-estimation yields a constant elasticity estimate of 1.002 (SE = 0.023), implying that on average, the two measures are virtually unit elastic. LOO computation does not purge MS23's proxy of correlations with county-level EHE; LOO EHE and county-level EHE are practically identical.

4 Direct Measures of Innovation Exposure

As discussed in Section 3.1, it is not necessary to proxy innovation exposure with LOO EHE, as MS23 possess data on multiple direct measures of innovation. Section IV of MS23 shows that county-level EHE induces increases in two forms of innovation. First, Table I and Figure IV show that crops whose croplands are exposed to more extreme heat see increases in crop variety development. Repository dataset `crop_level_data.dta` stores crop-decade panel data on $\text{NCrops}_{k,t}$, the number of crop varieties listed on the U.S. Department of Agriculture's *Variety Name List* for crop k in decade t. Second, Table II and Figure V show that crops whose croplands are exposed to more extreme heat see increases in associated patents that are related to climate change. `crop_level_data.dta` stores crop-level data on PatentsPre_k (the number of climate change-related patents associated with crop k prior to 1960, stored as `tot_1960_cc_USA`) and PatentsPost_k (the number of climate change-related patents associated with crop k between 1960-2020, stored as `tot_1960_2020_USA_cc`).[5]

I use these crop-level innovation variables to construct direct measures of innovation

[5]Though I contacted the authors to request crop-decade panel data on patent development, the authors informed me that crop-decade panel data was never stored, and patent data was only scraped for use in LD specifications.

exposure in the county-decade panel data. First, I compute *variety exposure*:

$$\text{VarietyExposure}_{i,t} = \sum_k \left[\frac{\text{NCrops}_{k,t} \times \text{Area}^{\text{Pre}}_{i,k}}{\sum_{k'} \text{Area}^{\text{Pre}}_{i,k'}} \right]. \tag{E7}$$

This measure is constructed similarly to $\text{ExtremeExposure}_{i,t}$, as it is an area-weighted average of crop variety (rather than EHE). The same is true of my second direct innovation measure, which I term *patent exposure*:

$$\text{PatentExposure}_{i,t} = \begin{cases} \sum_k \left[\frac{\text{PatentsPre}_k \times \text{Area}^{\text{Pre}}_{i,k}}{\sum_{k'} \text{Area}^{\text{Pre}}_{i,k'}} \right] & \text{if } t = 1950 \\ \sum_k \left[\frac{\text{PatentsPost}_k \times \text{Area}^{\text{Pre}}_{i,k}}{\sum_{k'} \text{Area}^{\text{Pre}}_{i,k'}} \right] & \text{if } t = 2010 \end{cases}. \tag{E8}$$

Patent exposure is only defined for $t \in \{1950, 2010\}$, as data is only available on patenting in these two time periods. It is thus only possible to replicate LD estimates of Equation E1 using patent exposure.

One could argue that these direct measures of innovation exposure are inappropriate for use in models estimating Equation E1 because these direct measures are endogenously determined; indeed, MS23 find evidence that market innovations endogenously adapt to climate change. However, for the purposes of estimating a model of the form in Equation E1, $\text{VarietyExposure}_{i,t}$ and $\text{PatentExposure}_{i,t}$ are *per se* less endogenous measures of innovation exposure than LOO EHE. The reason why is intuitive. To whatever extent LOO EHE reflects innovation exposure, the latent innovation exposure captured by LOO EHE is subject to the same endogenous data-generating process as the latent innovation exposure captured by direct measures of innovation. However, LOO heat exposure reflects *additional* endogeneity arising from its strong relationships with both local and national climate trends, as demonstrated in Section 3.1.

Replications of the model in Equation E1 that replace LOO EHE with $\text{VarietyExposure}_{i,t}$ or $\text{PatentExposure}_{i,t}$ thus provide less biased estimates of the mitigatory impacts of innovation on climate-driven AL devaluation. Section 5.2 also reports instrumental variables (IV) specifications that exploit whatever exogenous variation LOO EHE induces in innovation. The results from these IV models do not qualitatively differ from the results arising from models that omit the IV strategy.

5 Results

5.1 Reduced-Form Estimates

[Table R–III about here]

Table R–III shows the results of models estimating Equation E1, where LOO EHE is replaced with $\text{VarietyExposure}_{i,t}$. Replacing MS23's proxy with a direct measure of innovation exposure virtually eliminates the moderating effects found in Table R–I. Across all models in Table R–III, no moderating effect estimate is statistically significantly different from zero.

The moderating effect estimates in Table R–III are microscopic compared to those estimates in Table R–I. This is not due to a difference in units; though the partial correlation coefficients of the moderating effect estimates in Table R–I, Panel C range from $0.091r$ to $0.425r$, those coefficients in Table R–III, Panel B range from $-0.137r$ to $0.034r$. Partial correlation coefficients do not lend well to linear comparisons; $r = 0.015$ is not one tenth of $r = 0.15$ in the same way that $r = 1.5$ is not ten times $r = 0.15$. However, standardized coefficients do permit such linear comparisons; the standardized coefficient estimates of moderating effects in Table R–III, Panel C are at least 99.8% less, and at least 93% smaller, than those moderating effect estimates in Table R–I, Panel D.

[Table R–IV about here]

The same reduction in moderating effect estimates occurs when LOO EHE is replaced with $\text{PatentExposure}_{i,t}$ rather than $\text{VarietyExposure}_{i,t}$. Table R–IV shows LD specifications estimating Equation E1 with $\text{PatentExposure}_{i,t}$ replacing LOO EHE. Again, no moderating effect estimates from this specification are statistically significantly different from zero. Partial correlation coefficients on the moderating effect estimates in this table range from $-0.136r$ to $0.01r$. The standardized coefficient estimates of moderating effects in Table R–IV, Panel C are at least 99.8% less, and at least 98.5% smaller, than those moderating effect estimates in Table R–I, Panel D. Across both direct measures of innovation exposure, there is no statistically significant evidence that innovation moderates EHE impacts on AL values.

[Figure R-IV about here]

Figure R-IV plots HTEs of county-level EHE on AL values for selected quantiles of different moderating variables. The left graph in Figure R-IV provides a direct reproduction of the right graph in Figure R-I to offer a reference of MS23's original estimates in Figure VI. The middle and right graphs in Figure R-IV, respectively constructed from the Model 1 estimates in Tables R–III and R–IV, show that the impact of EHE on AL values is much more flat in variety exposure and patent exposure than it is in LOO EHE. Though the left graph shows that the marginal AL devaluation impacts of local EHE diminish for higher quantiles of LOO EHE, becoming not statistically significantly different from zero for sufficiently high quantiles, such marginal impacts do not increase at all over the distribution of patent exposure. In fact, the right graph of Figure R-IV implies that marginal land devaluation impacts of local EHE become slightly more severe for counties with higher patent exposure.

The middle graph in Figure R-IV does somewhat emulate the left graph; the marginal impact of local EHE on AL values is no longer statistically significantly different from zero for sufficiently high quantiles of variety exposure. However, as Table R–III shows, this is not because variety exposure significantly moderates the AL devaluation impacts of EHE upward; such marginal impacts are roughly as flat in variety exposure as they are in patent exposure (see also Table R–IV). Rather, this loss of a statistically significant climate-driven AL devaluation impact reflects the sparsity of data in the top quantiles of variety exposure, which substantially expands the confidence intervals around the marginal effect estimates in these quantiles. That is, the loss of a statistically significant marginal EHE impact for top quantiles of variety exposure reflects noise rather than meaningful moderating impacts.

5.2 Instrumental Variables Estimates

As discussed in Section 4, one argument for proxying innovation exposure with LOO EHE is that innovation exposure is endogenously determined, whereas LOO EHE is plausibly exogenous. To show that the results in Section 5.1 are not driven by the endogenous determination of my direct innovation measures, I estimate IV models of Equation E1 that instrument innovation exposure (defined as either variety or patent exposure) and its interaction with

$\text{ExtremeExposure}_{i,t}$ using a second-order polynomial of LOO EHE. This specification choice reflects the intuition that if LOO EHE is a good exogenous proxy for innovation exposure, then it should also be a good instrument for innovation exposure.

Considering this IV framework provides additional intuition for why LOO EHE is an inappropriate proxy for innovation exposure. In particular, a clear exclusion restriction violation arises, as LOO EHE is naturally expected to impact AL values through mechanisms other than innovation exposure. Specifically, as established in Section 3.1, LOO EHE will impact AL values through county-level EHE because LOO EHE reflects national and global climate trends that directly impact county-level EHE. Prior literature also establishes that using temperature as an instrument is known to induce many potential exclusion restriction violations beyond this relatively simple case (see Mellon 2023).

Appendix Tables A-III and A-IV respectively replicate Tables R–III and R–IV after instrumenting innovation exposure and its interaction with county-level EHE using a second-order polynomial in LOO EHE. Though the moderating effect estimates in Tables A-III and A-IV are generally larger than those in R–III and R–IV (respectively), the first-stage F-statistics show that these different effect sizes are biased not only by the aforementioned exclusion restriction violations, but also by weak instruments. The second-order polynomial of LOO heat exposure is a relatively weak instrument for innovation exposure and its interaction with $\text{ExtremeExposure}_{i,t}$; Kleibergen & Paap (2006) first-stage F-statistics in Tables A-III and A-IV range from 0.135 to 7.583. This provides further evidence that LOO EHE is an inappropriate proxy for innovation exposure, as LOO EHE is not a particularly strong predictor of innovation exposure.

Despite the increased size of the moderating effect estimates, none of the estimates in Tables A-III or A-IV provide clear support for a mitigatory moderating impact of innovation exposure on climate-driven land devaluation. The moderating effect estimates in Tables A-III and A-IV are very noisy. The SEs of the standardized moderating effect estimates in Panel C of Table A-III (Table A-IV) exceed those of the respective estimates in Panel C of Table R–III (Table R–IV) by at least 277% (328%). Further, the moderating effect estimates in Table A-IV are all negative; if taken at face value, this would imply that counties with higher cropland exposure to climate change-related patents experience *more* AL devaluation from EHE. However, none of the moderating effect estimates in Tables A-III or A-IV are statistically significantly different from zero.

6 Conclusion

This paper shows that MS23's estimates of the mitigatory moderating impact of technological market adaptations on EHE-induced AL devaluation are largely an artefact of an inappropriate proxy for innovation exposure. When I re-estimate MS23's models using direct measures of innovation, the mitigatory effect estimates I obtain are at least 99.8% less than those obtained by MS23, and none are statistically significantly different from zero. Contrary to MS23's key conclusions, my results suggest that technological market adaptations have little capacity to mitigate the agricultural damage induced by climate change. These conclusions reflect several prior studies that estimate similar mitigatory effects (e.g., see Hornbeck 2012; Aragón, Oteiza, & Rud 2021).

The findings in this paper cast doubt on more than just MS23's main estimates of technological innovation's moderating influence on EHE-induced AL devaluation. Principally, MS23's projections of aggregate historical and future climate change damage mitigation from technological innovation depend on their estimates in Table III (see pgs. 685 and 690-691). The fact that the moderating effect estimates obtained using direct measures are at least 99.8% less than the estimates obtained using MS23's proxy imply that the projected mitigatory benefits of technological innovations likely decrease to similar degrees.[6] However, more importantly, my findings show that one should not put too much faith in the capacity of technological market innovations to substantially mitigate the agricultural harms of climate change. This last point is critically important to those seeking to compute – or decide – optimal investment levels for abating climate change.

Author affiliation: Vrije Universiteit Amsterdam; School of Business and Economics; Department of Ethics, Governance, and Society.

[6] These projections are not readily replicable using MS23's replication repository, as MS23 do not fully disclose the specifications, nor the extraction procedures, by which the inputs necessary to generate aggregate effect projections in Figures VII or VIII are obtained.

Appendix

Replication Package Item	Fully	Partial	No
Raw data provided	X		
Analysis data provided	X		
Cleaning code provided		X	
Analysis code provided		X	
Reproducible from raw data		X	
Reproducible from analysis data		X	

Note: This table summarizes the reproducibility of MS23's published findings based on the replication repository in Moscona & Sastry (2022).

Table A-I: Reproducibility of Published Findings from Replication Repository

	Linear Coefficient	Elasticity
LOO extreme heat exposure	0.994	1.002
	(0.018)	(0.023)
Observations	21027	21027

Note: Results are based on a simple random effects panel data regression where county-level EHE is the independent variable. The elasticity estimate is obtained via the `margins, eyex()` post-estimation command in Stata.

Table A-II: Relationship Between Extreme Heat Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Raw coefficients							
County-level extreme exposure	0.00068	0.00089	0.00054	0.00101	0.00072	0.00062	0.00123
	(0.00026)	(0.00027)	(0.00023)	(0.00046)	(0.00035)	(0.00044)	(0.00068)
	[0.01098]	[0.00141]	[0.02083]	[0.03111]	[0.04201]	[0.16249]	[0.07245]
County-level extreme exposure × variety exposure	0.04751	-0.1973	-0.07448	-0.3257	0.12248	0.13951	-0.05239
	(0.25192)	(0.24639)	(0.18544)	(0.42494)	(0.38848)	(0.52994)	(0.71966)
	[0.8508]	[0.42526]	[0.68887]	[0.4453]	[0.75325]	[0.79252]	[0.94201]
Panel B: Partial correlations							
County-level extreme exposure	0.25721	0.31982	0.23441	0.21905	0.2069	0.07626	0.09798
	(0.09581)	(0.0921)	(0.09696)	(0.09767)	(0.09821)	(0.05432)	(0.05411)
	[0.00857]	[0.00078]	[0.01753]	[0.02724]	[0.03777]	[0.16127]	[0.07109]
County-level extreme exposure × variety exposure	0.01935	-0.08244	-0.04124	-0.07888	0.03233	0.01438	-0.00398
	(0.10256)	(0.1019)	(0.10242)	(0.10196)	(0.10249)	(0.05462)	(0.05463)
	[0.85077]	[0.42054]	[0.68812]	[0.44106]	[0.75312]	[0.79249]	[0.94201]
Panel C: Standardized coefficients							
County-level extreme exposure	0.54334	0.71173	0.42841	0.80664	0.57322	0.51363	1.0248
	(0.20944)	(0.21633)	(0.18228)	(0.36863)	(0.2781)	(0.36692)	(0.56871)
	[0.01098]	[0.00141]	[0.02083]	[0.03111]	[0.04201]	[0.16249]	[0.07245]
County-level extreme exposure × variety exposure	0.03334	-0.13843	-0.05221	-0.22851	0.08586	0.12731	-0.04781
	(0.17674)	(0.17287)	(0.12999)	(0.29814)	(0.27233)	(0.4836)	(0.65673)
	[0.8508]	[0.42526]	[0.68887]	[0.4453]	[0.75325]	[0.79252]	[0.94201]
First-stage F	3.097	2.545	7.583	2.425	3.361	0.307	0.143
Estimation type	LD	LD	LD	LD	LD	Panel	Panel
County fixed effects	X	X	X	X	X	X	X
State × decade fixed effects	X	X	X	X	X	X	X
Weighted by agricultural land area		X					X
Output prices and interactions			X		X		
Avg. temp. (° C) and interactions				X	X		
Observations	6000	6000	5990	6000	5990	20966	20966
A^2	-0.881	-1.259	-0.491	-2.327	-1.3	-0.35	-1.422

Note: The dependent variable in all models is logarithmic AL values. Estimates of the specification in Equation E1, where LOO EHE is replaced with $\text{VarietyExposure}_{i,t}$, and $\text{VarietyExposure}_{i,t}$ and $(\text{VarietyExposure}_{i,t} \times \text{ExtremeExposure}_{i,t})$ are instrumented by a second-order polynomial of LOO EHE, are presented alongside SEs double-clustered at the county and state-year levels in parentheses, as well as p-values in brackets. F-statistics are computed in accordance with Kleibergen & Paap (2006).

Table A-III: Mitigatory Impacts of Variety Exposure, IV Estimates

	(1)	(2)	(3)	(4)	(5)
Panel A: Raw coefficients					
County-level extreme exposure	0.000233	0.001285	0.000239	0.000256	3e-04
	(0.000102)	(0.002324)	(0.000123)	(9.5e-05)	(0.000161)
	[0.024276]	[0.5816]	[0.055049]	[0.008536]	[0.064954]
County-level extreme exposure ×	-0.083581	-0.113446	-0.124031	-0.184512	-0.093768
patent exposure	(0.276747)	(1.075576)	(0.22589)	(0.284015)	(0.33166)
	[0.763303]	[0.916222]	[0.584243]	[0.517481]	[0.778005]
Panel B: Partial correlations					
County-level extreme exposure	0.228656	0.05664	0.195444	0.265671	0.188152
	(0.097234)	(0.102269)	(0.098679)	(0.095356)	(0.098966)
	[0.020758]	[0.580993]	[0.050528]	[0.006441]	[0.060309]
County-level extreme exposure ×	-0.031001	-0.010822	-0.056423	-0.066802	-0.029019
patent exposure	(0.102499)	(0.102586)	(0.102271)	(0.10214)	(0.102511)
	[0.762972]	[0.916207]	[0.582447]	[0.514676]	[0.777732]
Panel C: Standardized coefficients					
County-level extreme exposure	0.550315	3.040981	0.565809	0.605254	0.710472
	(0.240384)	(5.499604)	(0.291293)	(0.225339)	(0.380496)
	[0.024276]	[0.5816]	[0.055049]	[0.008536]	[0.064954]
County-level extreme exposure ×	-0.05864	-0.079593	-0.086946	-0.129454	-0.065732
patent exposure	(0.194166)	(0.754625)	(0.158351)	(0.199265)	(0.232496)
	[0.763304]	[0.916222]	[0.584243]	[0.517481]	[0.778006]
First-stage F	6.465	0.135	5.304	5.597	2.311
Estimation type	LD	LD	LD	LD	LD
County fixed effects	X	X	X	X	X
State × decade fixed effects	X	X	X	X	X
Weighted by agricultural land area		X			
Output prices and interactions			X		X
Avg. temp. (° C) and interactions				X	X
Observations	6000	6000	5990	6000	5990
A^2	-0.936	-27.149	-0.909	-1.186	-1.534

Note: The dependent variable in all models is logarithmic AL values. Estimates of the specification in Equation E1, where LOO EHE is replaced with $\text{PatentExposure}_{i,t}$, $t \in \{1950, 2010\}$, and $\text{PatentExposure}_{i,t}$ and $\left(\text{PatentExposure}_{i,t} \times \text{ExtremeExposure}_{i,t}\right)$ are instrumented by a second-order polynomial of LOO EHE, are presented alongside SEs double-clustered at the county and state-year levels in parentheses, as well as p-values in brackets. F-statistics are computed in accordance with Kleibergen & Paap (2006).

Table A-IV: Mitigatory Impacts of Patent Exposure, IV Estimates

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Tables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Published estimates							
County-level extreme exposure	-0.851	-1.519	-0.825	-0.862	-0.786	-0.232	-0.39
	(0.211)	(0.24)	(0.203)	(0.238)	(0.226)	(0.107)	(0.132)
County-level extreme exposure ×	0.249	0.425	0.237	0.251	0.23	0.0912	0.128
innovation exposure	(0.0757)	(0.0745)	(0.0728)	(0.0791)	(0.0762)	(0.0315)	(0.0321)
Panel B: Reproductions							
County-level extreme exposure	-0.851	-1.519	-0.825	-0.862	-0.786	-0.232	-0.39
	(0.211)	(0.24)	(0.203)	(0.238)	(0.226)	(0.107)	(0.132)
	[0]	[0]	[0]	[0]	[0.001]	[0.031]	[0.003]
County-level extreme exposure ×	0.249	0.425	0.237	0.251	0.23	0.0912	0.128
innovation exposure	(0.0757)	(0.0745)	(0.0728)	(0.0791)	(0.0762)	(0.0315)	(0.0321)
	[0.001]	[0]	[0.002]	[0.002]	[0.003]	[0.004]	[0]
Panel C: Partial correlations							
County-level extreme exposure	-0.454	-0.854	-0.459	-0.401	-0.382	-0.119	-0.163
	(0.081)	(0.028)	(0.081)	(0.086)	(0.088)	(0.054)	(0.053)
	[0]	[0]	[0]	[0]	[0]	[0.028]	[0.002]
County-level extreme exposure ×	0.32	0.505	0.317	0.31	0.295	0.156	0.213
innovation exposure	(0.092)	(0.076)	(0.092)	(0.093)	(0.094)	(0.053)	(0.052)
	[0.001]	[0]	[0.001]	[0.001]	[0.002]	[0.004]	[0]
Panel D: Standardized coefficients							
County-level extreme exposure	-0.597	-1.066	-0.579	-0.605	-0.551	-0.212	-0.355
	(0.148)	(0.168)	(0.142)	(0.167)	(0.158)	(0.098)	(0.121)
	[0]	[0]	[0]	[0]	[0.001]	[0.031]	[0.003]
County-level extreme exposure ×	0.603	1.028	0.572	0.607	0.554	0.274	0.387
innovation exposure	(0.183)	(0.18)	(0.176)	(0.191)	(0.184)	(0.095)	(0.097)
	[0.001]	[0]	[0.002]	[0.002]	[0.003]	[0.004]	[0]
Estimation type	LD	LD	LD	LD	LD	Panel	Panel
County fixed effects	X	X	X	X	X	X	X
State × decade fixed effects	X	X	X	X	X	X	X
Weighted by agricultural land area		X					X
Output prices and interactions			X		X		
Avg. temp. (° C) and interactions				X	X		
Observations (published)	6000	6000	5990	6000	5990	20931	20931
Observations (reproduction)	6000	6000	5990	6000	5990	20966	20966
R^2	0.989	0.991	0.989	0.989	0.989	0.979	0.984

Note: The dependent variable in all models is logarithmic AL values. Estimates of the specification in Equation E1 are presented alongside SEs double-clustered at the county and state-year levels in parentheses, as well as p-values in brackets. These values are not reported in Panel A, as they are not reported in the published estimates in Table III.

Table R–I: Reproduction of Table III

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Raw coefficients							
County-level extreme exposure	-0.898	-0.954	-0.866	-0.867	-0.761	-0.223	-0.169
	(0.16)	(0.243)	(0.162)	(0.19)	(0.179)	(0.09)	(0.116)
	[0]	[0]	[0]	[0]	[0]	[0.013]	[0.146]
(County-level extreme exposure)^2	0.058	0.061	0.063	0.068	0.064	0.02	0.01
	(0.018)	(0.028)	(0.016)	(0.016)	(0.016)	(0.008)	(0.01)
	[0.002]	[0.031]	[0]	[0]	[0]	[0.016]	[0.33]
Panel B: Partial correlations							
County-level extreme exposure	-0.701	-0.441	-0.656	-0.529	-0.486	-0.137	-0.08
	(0.052)	(0.083)	(0.058)	(0.074)	(0.078)	(0.054)	(0.054)
	[0]	[0]	[0]	[0]	[0]	[0.011]	[0.142]
(County-level extreme exposure)^2	0.316	0.219	0.37	0.396	0.372	0.131	0.053
	(0.092)	(0.098)	(0.089)	(0.087)	(0.088)	(0.054)	(0.054)
	[0.001]	[0.027]	[0]	[0]	[0]	[0.015]	[0.329]
Panel C: Standardized coefficients							
County-level extreme exposure	-0.63	-0.67	-0.607	-0.608	-0.533	-0.204	-0.154
	(0.113)	(0.17)	(0.114)	(0.133)	(0.125)	(0.082)	(0.105)
	[0]	[0]	[0]	[0]	[0]	[0.013]	[0.146]
(County-level extreme exposure)^2	0.271	0.288	0.298	0.32	0.302	0.116	0.06
	(0.083)	(0.132)	(0.077)	(0.076)	(0.077)	(0.048)	(0.061)
	[0.002]	[0.031]	[0]	[0]	[0]	[0.016]	[0.33]
Estimation type	LD	LD	LD	LD	LD	Panel	Panel
County fixed effects	X	X	X	X	X	X	X
State × decade fixed effects	X	X	X	X	X	X	X
Weighted by agricultural land area		X					X
Output prices and interactions			X		X		
Avg. temp. (° C) and interactions				X	X		
Observations	6000	6000	5990	6000	5990	20966	20966
R^2	0.988	0.99	0.989	0.989	0.989	0.979	0.984

Note: The dependent variable in all models is logarithmic AL values. Estimates of the specification in Equation E6 are presented alongside SEs double-clustered at the county and state-year levels in parentheses, as well as p-values in brackets.

Table R–II: Fitting a Second-Order Polynomial in Extreme Heat Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Raw coefficients							
County-level extreme exposure	-0.3967733	-0.5056133	-0.4126515	-0.30271	-0.3169444	-0.0228589	-0.0885235
	(0.1107134)	(0.1332734)	(0.1068332)	(0.1212079)	(0.1223538)	(0.0663453)	(0.0962329)
	[0.0005366]	[0.0002609]	[0.0002049]	[0.0142292]	[0.0110957]	[0.7306531]	[0.3582927]
County-level extreme exposure ×	-3.5e-06	5.4e-06	-1.86e-05	-1e-06	-2.67e-05	-6.2e-06	9e-07
variety exposure	(9.6e-06)	(1.61e-05)	(2.38e-05)	(9.2e-06)	(2.03e-05)	(7.2e-06)	(1.1e-05)
	[0.7175476]	[0.7372921]	[0.4368398]	[0.9092712]	[0.1905351]	[0.3957842]	[0.9383229]
Panel B: Partial correlations							
County-level extreme exposure	-0.3953861	-0.4225602	-0.431632	-0.2650822	-0.2756833	-0.0188278	-0.0503225
	(0.0865587)	(0.0842783)	(0.0834832)	(0.0953884)	(0.0948003)	(0.0546165)	(0.0544975)
	[1.48e-05]	[2.5e-06]	[1.3e-06]	[0.0065729]	[0.0045277]	[0.7305154]	[0.356468]
County-level extreme exposure ×	-0.0372501	0.034496	-0.0803705	-0.0117239	-0.1365211	-0.0465052	0.0042307
variety exposure	(0.1024555)	(0.1024757)	(0.1019351)	(0.1025837)	(0.1006856)	(0.0545177)	(0.0546349)
	[0.7169847]	[0.7371415]	[0.4323979]	[0.9092525]	[0.1783406]	[0.3942519]	[0.9383224]
Panel C: Standardized coefficients							
County-level extreme exposure	-0.2783764	-0.3547386	-0.2892716	-0.2123816	-0.2221802	-0.02086	-0.0807825
	(0.0776766)	(0.0935047)	(0.0748909)	(0.0850395)	(0.0857709)	(0.0605437)	(0.0878177)
	[0.0005366]	[0.0002609]	[0.0002049]	[0.0142292]	[0.0110958]	[0.730653]	[0.3582926]
County-level extreme exposure ×	-0.005034	0.0078194	-0.0268635	-0.0015185	-0.0386643	-0.0094378	0.001311
variety exposure	(0.0138748)	(0.0232426)	(0.0344035)	(0.01329)	(0.0293264)	(0.0110998)	(0.0169298)
	[0.7175474]	[0.7372923]	[0.4368401]	[0.9092709]	[0.1905353]	[0.3957844]	[0.9383227]
Estimation type	LD	LD	LD	LD	LD	Panel	Panel
County fixed effects	X	X	X	X	X	X	X
State × decade fixed effects	X	X	X	X	X	X	X
Weighted by agricultural land area		X					X
Output prices and interactions			X		X		
Avg. temp. (° C) and interactions				X	X		
Observations	6000	6000	5990	6000	5990	20966	20966
R^2	0.988	0.99	0.989	0.988	0.989	0.979	0.984

Note: The dependent variable in all models is logarithmic AL values. Estimates of the specification in Equation E1, where LOO EHE is replaced with $\text{VarietyExposure}_{i,t}$, are presented alongside SEs double-clustered at the county and state-year levels in parentheses, as well as p-values in brackets.

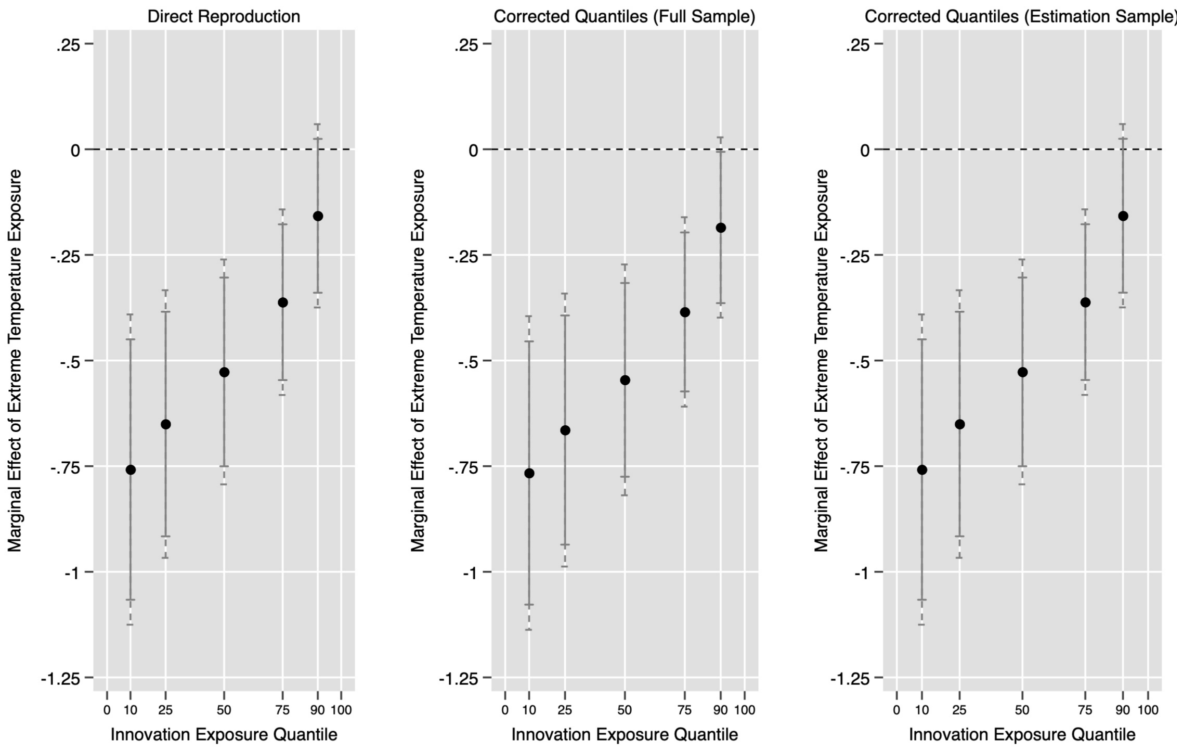
Table R–III: Mitigatory Impacts of Variety Exposure

	(1)	(2)	(3)	(4)	(5)
Panel A: Raw coefficients					
County-level extreme exposure	-0.4220814	-0.5217386	-0.4485648	-0.3207568	-0.3215077
	(0.1113025)	(0.1388546)	(0.1133408)	(0.119662)	(0.1292944)
	[0.0002624]	[0.0002962]	[0.000146]	[0.0086664]	[0.014641]
County-level extreme exposure ×	-2e-06	4e-07	-7.9e-06	-8e-07	-9.8e-06
patent exposure	(2.7e-06)	(4.6e-06)	(8.5e-06)	(2.5e-06)	(7.5e-06)
	[0.4723702]	[0.9231358]	[0.3545097]	[0.7396941]	[0.1916005]
Panel B: Partial correlations					
County-level extreme exposure	-0.4223497	-0.4177993	-0.4443255	-0.286046	-0.2638545
	(0.0842965)	(0.0846887)	(0.0823424)	(0.094203)	(0.0954551)
	[2.5e-06]	[3.4e-06]	[5e-07]	[0.0030893]	[0.0068548]
County-level extreme exposure ×	-0.0742286	0.0099249	-0.0958975	-0.0342088	-0.1361847
patent exposure	(0.1020325)	(0.1025877)	(0.1016543)	(0.1024778)	(0.100695)
	[0.4687091]	[0.9231321]	[0.3478854]	[0.7392535]	[0.179443]
Panel C: Standardized coefficients					
County-level extreme exposure	-0.2961326	-0.3660521	-0.314447	-0.2250432	-0.2253791
	(0.0780899)	(0.0974205)	(0.0794527)	(0.0839549)	(0.0906363)
	[0.0002624]	[0.0002962]	[0.000146]	[0.0086664]	[0.0146411]
County-level extreme exposure ×	-0.0086029	0.0019263	-0.0343705	-0.0036543	-0.0425796
patent exposure	(0.0119236)	(0.0199124)	(0.0369407)	(0.0109664)	(0.0323744)
	[0.47237]	[0.9231359]	[0.3545099]	[0.7396939]	[0.1916007]
Estimation type	LD	LD	LD	LD	LD
County fixed effects	X	X	X	X	X
State × decade fixed effects	X	X	X	X	X
Weighted by agricultural land area		X			
Output prices and interactions			X		X
Avg. temp. (° C) and interactions				X	X
Observations	6000	6000	5990	6000	5990
R^2	0.988	0.99	0.989	0.988	0.989

Note: The dependent variable in all models is logarithmic AL values. Estimates of the specification in Equation E1, where LOO EHE is replaced with $\text{PatentExposure}_{i,t}$ and $t \in \{1950, 2010\}$, are presented alongside SEs double-clustered at the county and state-year levels in parentheses, as well as p-values in brackets.

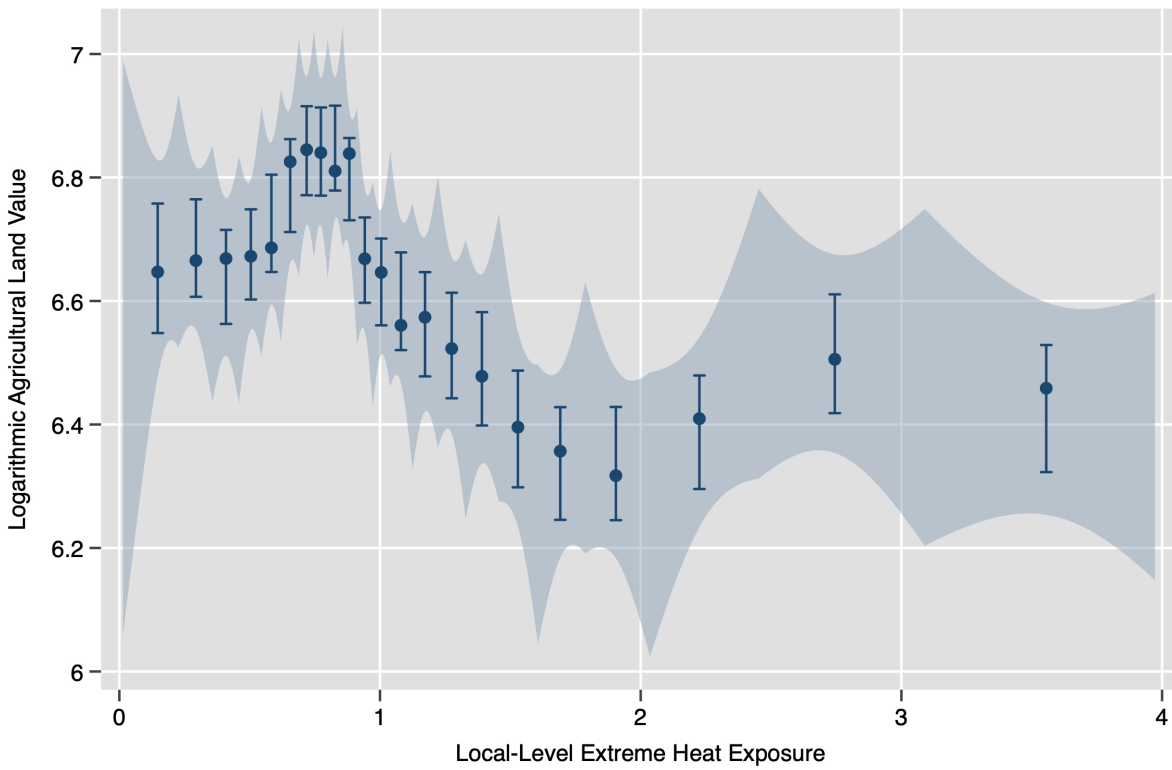
Table R–IV: Mitigatory Impacts of Patent Exposure

Figures



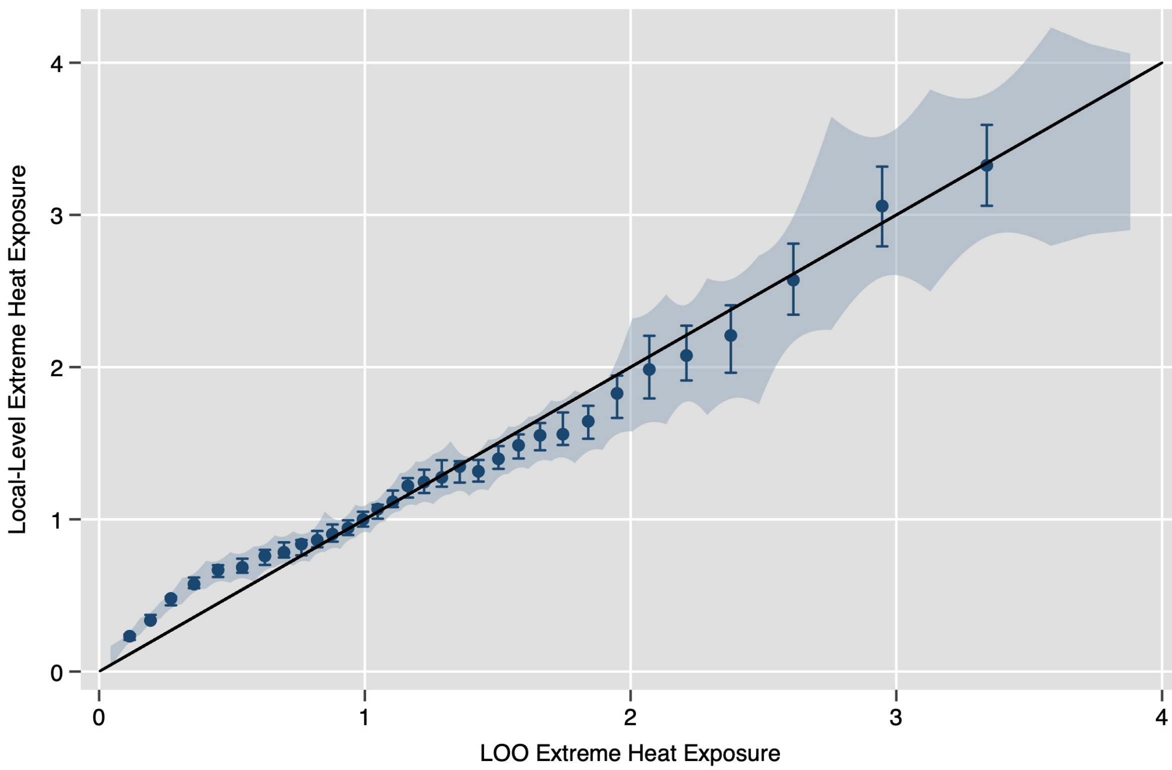
Note: The left graph reproduces Figure VI from MS23, while the center and right graphs correct the hard-coded quantiles used to construct the original graphs. Bars represent 90% and 95% confidence intervals. Estimates are based on Table R–I, Panel B, Model 1.

Figure R-I: Reproduction and Corrections of MS23's Figure VI



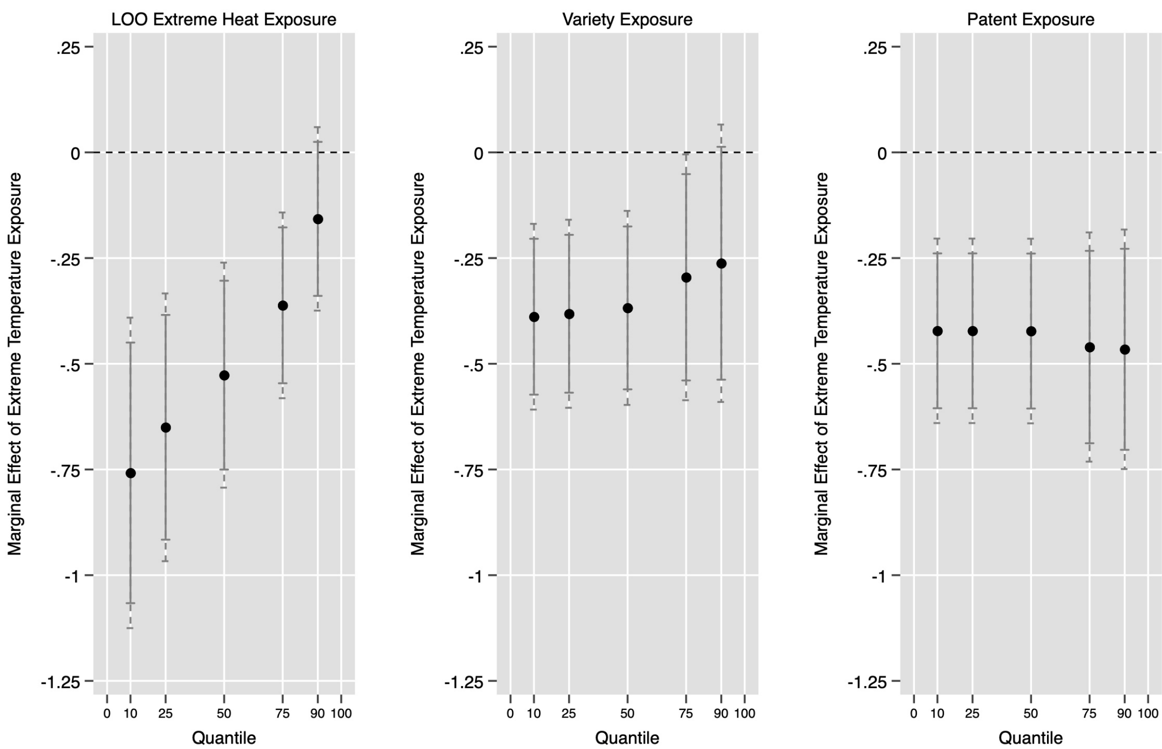
Note: The graph shows a binscatter regression plot (see Cattaneo et al. 2024) showing the relationship between logarithmic AL values and county-level EHE for $\text{ExtremeExposure}_{i,t} \in [0, 4]$; this restriction, instituted to improve interpretability, covers 95.3% of the distribution of $\text{ExtremeExposure}_{i,t}$. Confidence bands and intervals are constructed with SEs clustered at the county level.

Figure R-II: Nonlinear Dynamics of Agricultural Land Value and Local Extreme Heat Exposure



Note: The graph shows a binscatter regression plot (see Cattaneo et al. 2024) showing the relationship between county-level EHE and LOO EHE. LOO EHE is restricted to $[0, 4]$ to improve interpretability; this range covers 98.4% of the distribution of LOO EHE. Confidence bands and intervals are constructed with SEs clustered at the county level. A simple 45-degree line is appended to the graph for reference.

Figure R-III: Relationship between County-Level and LOO Extreme Heat Exposure



Note: The left graph reproduces the right graph from Figure R-I, while the center and right graphs display extrapolated marginal impacts of county-level EHE on AL values for selected quantiles of different moderators. The middle and right graphs are respectively constructed based on Model 1 estimates from Tables R–III and R–IV, Panel B.

Figure R-IV: HTEs of Extreme Heat Exposure