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Why Do Econometric Studies Disagree on the Effect of Warming on Agricultural Output? A Meta-Analysis

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Abstract

Having robust estimates of how global warming affects agricultural production is important for developing informed policies in response to food security, but the existing studies have been at odds on what this effect might be. This article conducts a meta-analysis based on 130 primary econometric studies to better understand the conflict among the existing estimates of warming on agriculture. We find that the difference in econometric model specification is an important source of disagreement, and that this disagreement can be greatly reduced if the studies model temperature nonlinearly, use a growing season temperature measure, and cross-sectional data which captures adaptations. (JEL Q15, Q51, Q54)

Key words: Climate change impact, Agriculture, Meta-analysis, Inconsistency

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1. Introduction

There is a global concern that climate change could cause severe shortages in the world's food supply (Conway and Toenniessen 1999, Lobell and Asner 2003, Brown and Funk 2008). To address this threat, policy makers would need to be informed by robust empirical evidence on the effect that global warming has on agricultural production. However, in the applied econometrics literature, there is much contention on what this effect might be or if it even exists (see, for example, Mendelsohn, Nordhaus, and Shaw 1994, Schlenker and Roberts 2006, Deschênes and Greenstone 2007, Schlenker and Roberts 2009, Nelson et al. 2014). Identifying the sources of this dispute can enable us to better understand how disagreements among studies on the effects of climate change may arise, construct a more complete picture on the true effect of climate change, and is itself a useful exercise for guiding future work on modelling the relationship between climate change and agriculture.

Existing research on the effect of global warming on agricultural output is based either on a simulation or an econometric approach (Deschênes and Greenstone 2007, Robertson et al. 2013). The simulation approach simulates the effect of climatic variables on crop yield using what are known as process-based crop growth models (see, for example, Adams et al. 1990). The econometric approach, on the other hand, estimates the response of crop yield to climate change by conducting a regression analysis on the relationship between historical climate and crop production (see, for example, Deschênes and Greenstone 2007). In the simulation based literature, there is much consistency in the predicted effect of global warming, in that global warming will lead to positive yield changes in high latitudes while causing damages in low latitudes (Rosenzweig and Parry (1994)). However, in the econometric based literature, there is much disagreement on how warming would affect agriculture, even with respect to places with similar latitudes.

For example, in the 130 econometric based studies we surveyed, 31.4% of them reported a positive and statistically significant effect of warming on crop yield for low latitude regions and 25.6% reported a statistically insignificant effect. Only 43% of these studies reported a negative and statistically significant effect, which is what simulation based studies had predicted for the low latitudes.[1] In the econometric based literature, the estimates on the effect of warming were often mixed. On a topic as important as global warming, such mixed messages may cause confusion to policy makers seeking to get their response to climate change right.

In this paper, our objective is to examine the sources of the disagreement among econometric based studies on how global warming affects agricultural output. To do so, we conduct a meta-analysis based on 130 primary studies, where we construct a meta-regression model that uses their econometric estimates (of the effect of warming on agriculture) as a meta-dependent variable and regressing it on several meta-independent variables with each capturing a feature associated with these studies (e.g. the geographical location where they are based on, the type of crops studied, and the specification of the econometric model, etc.).[2] It is generally believed that meta-analysis is an efficient approach for identifying features in the research design that are responsible for the excess variation among reported empirical

[1] See the data and statistical analysis section for more details

[2] As far as we know, the meta-analysis of applied econometric studies of the effect of warming on agriculture has not been reported. See Rosenzweig and Parry (1994) and Challinor et al. (2014) for meta-analysis of simulation studies. Since meta-analysis requires a common effect-size that is comparable among studies and this common effect-size is not exists between the simulation study and the econometric study, it is impossible to include both econometric and simulation studies in a single meta-analysis.

estimates on the same topic (Stanley and Jarrell 1989, Smith and Huang 1995, Klomp and De Haan 2010).

Our meta-regression shows that 64.8% of the disagreement among the 130 primary studies can be explained by the differences in model specification, biological characteristics of crops, study region and publication bias. Among these factors, we find that the difference in model specification explains the largest proportion of the disagreement. We also find that much of this disagreement can be reconciled if the primary studies had the following features – they modelled temperature nonlinearly, used a growing season temperature measure, and were based on cross-sectional data. In fact, if these characteristics were contained in the econometric study, it would generally produce predictions that are consistent with those of simulation based studies, in that warming will lead to positive yield changes in high latitude regions while causing crop damages in low latitude regions.

For the remainder of the paper, Section 2 introduces the meta-analysis approach that is used in this paper, Section 3 discusses the data and variables, Section 4 presents the meta-regression results, and Section 5 concludes.

2. The Meta-Regression Model

Meta-analysis is a method that uses existing results of similar empirical studies to answer a question on a given topic. It enjoys widespread use in economics since the 1990s, such as in the area of environmental and resource economics (Nelson and Kennedy 2009), and in international trade (Disdier and Head 2008). Meta-regression analysis is the most frequently used meta-analysis technique in economics. One of the main purposes of meta-regression is to identify features in the research design that are responsible for the excess variation among reported empirical estimates on the same topic. Understanding what these factors are can be immensely useful for guiding related work in the future (Stanley and Jarrell 1989, Smith and Huang 1995, Klomp and De Haan 2010).

In a meta-regression analysis, the dependent variable of the meta-regression is sometimes known as the "effect size", which is a quantity taken from the primary studies covered in the meta-analysis. The effect-size can be the regression coefficient, elasticity, *t*-statistic, significance level of a coefficient or other measures that are comparable across studies (Nelson and Kennedy 2009). The chosen effect-size for the meta-regression must be measuring the same thing as it will used to construct the meta-dependent variable (Stanley and Jarrell 1989).

In this study, the chosen effect size (or called meta-dependent variable hereinafter) is the *t*-statistic of the estimated coefficient of temperature on crop yield from the primary study.[3] This has two advantages over the estimated coefficient itself. Firstly, the *t*-statistic, unlike the estimated coefficient, has been normalized by the standard error, which reduces heteroscedasticity (Card and Krueger 1995, Becker and Wu 2007). Secondly, the *t*-statistic is truly comparable across studies, unlike the estimated coefficient which are generally incomparable as they depend on how the associated regressor is defined (e.g. different units). That being said, the *t*-statistic of the coefficient estimate and the estimate itself are closely related, in that the *t*-statistic is the standardized version of the latter. In meta-analyses, the *t*-statistic is frequently used (See, for example, Walker and Saw 1978, Card and Krueger 1995, Becker and Wu 2007) and we will follow the same approach here.

The meta-independent variables capture the various characteristics of the primary studies (e.g. the geographical location where they are based on, the type of crops studied, and the

[3] We focus on the effect of temperature because warming is the most important characteristic of climate change (IPCC 2007).

specification of the econometric model, etc.). Let T_i be the t-statistic of the regression coefficient from primary study i. Our meta-regression model is

$$T_i = \frac{\alpha_0}{se_i} + \sum_{k=1}^{K} \frac{\alpha_k Z_{ik}}{se_i} + \frac{\mu_i}{se_i} \qquad (i = 1, 2, \ldots L) \tag{1}$$

where se_i is the standard error of the coefficient estimate from study i, Z_{ik} is a K-vector of characteristics of the primary studies; α_0 is a constant term of the regression; α_k is the meta-regression coefficient on the k^{th} meta-independent variable, which captures the influence of study characteristic on the result heterogeneity across primary studies (Bel, Fageda, and Warner 2010); μ_i captures the remaining variation in T_i beyond the study characteristics under consideration.

3. Data and the Statistical Analysis

The validity of a meta-analysis depends on the completeness of the literature retrieval (Cavlovic et al. 2000). We carried out a broad and inclusive search of the rapidly growing econometric based literature that examines the effect of climate change on agricultural output. We searched the related published and unpublished studies from a variety of sources. For published papers, we looked up the Web of Science, Google Scholar, Academic OneFile, Academic Search Premier, JSTOR and Scopus, as well as the web sites of major publishers of academic journals, including Springer, Elsevier, Emerald, Blackwell, and Wiley. For unpublished papers (e.g. working papers, government reports, and dissertations), we searched using Google Scholar, SSRN, web sites of renowned research institutes, and the web sites of major government agencies. In all, our search took about seven months (June to December 2014) and covered more than 1000 papers, of which we selected 130 papers based on the following criteria.

First, we selected studies that contained some econometric analysis; those that were based purely on simulations were excluded.[4] Second, we chose studies that reported the effects of warming on the four major crops (maize, soybean, wheat and rice) or on the farmland values. Third, to ensure comparability, we used only estimates of the effect of mean temperature changes and selected studies that reported them.[5] Studies that solely reported the effects of extreme temperatures, such as the effects of minimum and maximum temperature, were excluded. Finally, to conduct weighted least squares regression and use the *t*-statistic as the meta-dependent variable, we selected studies that reported the variance of the coefficient of temperature measures or studies that enabled us to calculate the variance using other reported statistics.

[Figure 1]

From the 130 papers, we constructed a dataset with 341 observations.[6] Figure 1 shows the geographic distribution of the observations, which spread across 36 countries and 103 locations. Countries and regions that are more important agricultural producers are more frequently studied. For example, 22% of the sample is associated with the United States, which is the largest exporter of soybean, wheat and maize in the world market (U.S. EPA 2013), and 21% is associated with China, where agriculture is produced for its 1.3 billion population. Africa accounts for the largest proportion of the sample (27%), where food security in this region (IPCC 2007) could be a reason for why so much attention has been

[4] See footnote 2 for why we exclude simulation studies.

[5] The mean temperature can be measured by yearly mean temperature, yearly degree-day, growing season mean temperature or growing season degree-day.

[6] The observations exceed the number of paper collected because each paper often reports estimates associated with several different crops.

drawn to it. Besides the US, China and Africa, the European Union, India, and the rest of the world account for 6%, 7% and 17% of the sample respectively.

As discussed, we collected the *t*-statistic of temperature coefficient from the primary studies and constructed the meta-dependent variable from it. The magnitude of *t*-statistic is meaningful only when compared with the threshold *t*-value that stands for a particular significance level. Hence, we classify the *t*-statistic as positive and significant if it is above 1.68, negative and significant if it is below -1.68, and insignificant otherwise.[7] Figure 2 summarizes the meta-dependent variable across latitudes. Latitude is an important geographic characteristic as the simulation based literature suggests that warming mainly has negative effects on agricultural production in low latitudes and positive effects in high latitudes (Rosenzweig and Parry 1994, Challinor et al. 2014). However, as show in Figure 2, the econometric estimates of the effect of warming (i.e. the *t*-statistic of the coefficient estimate) corresponding to each sample latitude quartile group can be highly mixed.[8]

[Figure 2]

[7] The critical t-value of ±1.68 corresponds to a 10 percent significance level in the large sample climate change impact studies. We also tried to use the critical values that correspond to 5 percent or 1 percent significance levels, and the major conclusions of this study keep the same.

[8] We divide up the 341 observations into four sample latitude quartile groups by the quartiles of latitude of the sample and then calculated the percentage of observations that report different significance levels within each groups. The *low* sample latitude quartile group is defined as the observations from regions with latitudes below first quartile of the sample latitude (either from the Southern or Northern Hemisphere). The *low-middle* sample latitude quartile group is defined as the observations from regions with latitudes above first quartile but below the second quartile of the sample latitude, and so on.

For example, warming should have a negative effect on agricultural production in low latitude regions. However, for low latitude regions, as indicated by the *Low* group in Figure 2, 31.4% of the estimates based on studies on these regions show that warming has a positive and statistically significant effect (at the 10% level) and 25.6% of the estimates are statistically insignificant. Only 43% of the estimates are negative and statistically significant, which concur with what simulation based studies predict. Likewise, warming should have a positive effect in high latitude regions. But in Figure 2, the results associated with the *High* group show that a large proportion of the estimates based on studies on high latitude regions are negative.

The disagreement among the estimates from studies based on the same latitude group suggests that differences in model specification of the primary studies may be a reason for why different conclusions are reached. In empirical research, the set-up of an econometric model may influence the estimate of an effect that the model is designed to study; differences in model specification is often the main reason for why empirical research disagrees (Stanley and Jarrell 1989). On climate change research, it has been observed that the econometric based literature often suffers from estimation biases due to omitted variables (Lobell et al. 2005).

Besides differences in model specification, differences in certain study characteristics (e.g. the latitude of the region in which the study is based on) may also explain why the econometric estimates disagree, as Figure 2 shows. Firstly, differences in the chosen location of the studies can generate conflicting results. For instance, the marginal effect of warming in different latitudes should be different, as the mean temperature decreases with the increasing of latitude and the productivity response of crops to temperature is non-linear (Schlenker and Roberts 2009). Secondly, the biological difference among crops is another potential factor for the disparity among primary studies. For example, wheat has better productivity performance in cold climate than other major crops, and therefore, it is important to take crop type into account when studying the effect of warming on crop yields.

Thirdly, the conflicting results could be due to publication bias, which refers to the fact that research with 'statistically significant' results tend to be published than those with 'negative' results, and that what are deemed publishable could depend on the era during which the research is conducted (Rosenthal 1979).[9] Hence, the publication status (published or unpublished) and publication year can be used as meta-independent variables to capture the influence of publication bias.

[Table 1]

In Table 1, we list down the 10 characteristics among the 130 primary studies that we construct as meta-independent variables. Table 1 provides the definitions on the study characteristics, which are grouped into four categories: model specification, regional differences, publication bias, and biological differences. The summary statistics of meta-independent variables are documented in Table 2. Panel A of Table 2 provides the summary statistics of the primary studies' location and year of publication. In terms of location, the primary studies are conducted from the tropics to the cold zone. In terms of the year of publication, the first study was reported in 1992, while the mean year of the publications is 2010. Panel B of Table 2 provides the distribution of the dummy meta-dependent variables across 1 and 0. It shows that primary studies are quite different in terms of model specification, publication status and data set.

[Table 2]

[9] For example, at the early stage of climate change impact study, research that reported dramatic negative damages attracted more attentions. But in recent years, the possibility of mild negative effects and even positive effects has been recognized.

Table 3 shows that the design of a study can have a significant influence on the study's conclusion about the effect of warming on agricultural output. For example, for primary studies that model temperature nonlinearly, 27.0% reported significant and negative effects of warming, and 53.2% reported positive and significant effects. However, for studies that did not model temperature nonlinearly, 38.8% reported significant and negative effects, and only 22.4% reported positive and significant effects. Other study characteristics such as *control precipitation* and *publication status* also had a rather large influence on the estimates.

[Table 3]

4. Meta-Regression Results

Table 4 documents the regression estimates of the influence that the 10 meta-independent variables (see Table 1) have on the meta-dependent variable (the *t-statistic* of the coefficient associated with the temperature measure from the primary study). Column (1) presents our main regression result of Eq. (1). As a sensitivity check, we re-estimated Eq. (1) using a sample that excludes China (Column (2)), Africa (Column (3)) and the United States (Column (4)), which are the three most extensively examined regions among the primary studies. The estimates across Columns (1) to (4) are rather stable in terms of their signs, magnitude, and statistical significance. Because the results are robust, we will focus our discussion mainly on baseline regression from here onwards.

[Table 4]

Column (1) shows that the 10 meta-independent variables explain a significant proportion of the variation in the primary estimates. For example, the adjusted R^2 of 64.89% indicates that the 10 meta-independent variables account for 64.89% of the variation in the primary estimates. This is rather large for a meta-regression. For example, Nelson and Kennedy

(2009), who looked at 140 meta-analyses in environmental and resource economics, found that the average adjusted R^2 among these meta-analyses was only 48%.

Most of the meta-independent variables are statistically significant. The location where the primary studies are based on can influence the estimates of the effect of warming on crop yield. For instance, the coefficient of *latitude* is positive and statistically significant, which implies that studies based on higher latitude regions are more likely to report positive effects of warming than studies based on lower latitude regions. This result concurs with the simulation based literature, where based on crop growth models, it is found that warming will result in positive yield changes in the high latitudes while causing damages in the low latitudes (Rosenzweig and Parry 1994, Challinor et al. 2014).

Publication bias and biological differences in crops are also important in accounting for the disagreement among primary studies. Under the "Publication bias" category, the coefficient on *research time* is positive and statistically significant, which implies that studies that are more recently published tend to report positive effects than those published earlier. This may reflect an evolving preference by the research community for results of a certain nature. The coefficient of *publication status* is negative and statistically significant, which means the published papers or books are more likely to report negative effects than the unpublished materials. Under the "Biological differences" category, the significant coefficients on the dummies for *maize*, *soybean*, and *rice* but not *wheat* imply that the effects of warming can differ for different crops.

The specification of the econometric model has a strong influence on the eventual estimated effects of warming as well. Under the "Model specification" category, the variables *measures of output*, *non-linear setting*, *temperature measures* and *data types* are all positive and statistically significant. To investigate the relative importance of model specification in explaining the disparity among the primary studies, we conduct a regression analysis for each sub-category of variables. That is, for each sub-category regression, we include variables only from one of the four meta-independent categories (regression results not shown here to save space).[10] Comparing the adjusted R^2 across the four sub-category regressions, we find that model specification has the strongest influence on the primary estimates. In particular, differences in model specification can explain 30% of the disagreement among primary studies, whereas 15% of the disagreement can be explained by biological differences in crops, 12.4% by regional differences, and 9.8% by publication bias.

Given that differences in model specification account for the largest share of the disagreement, we investigate the extent to which these studies could be reconciled if they had adopted a certain set of specifications. Exploring different combinations of the variables and variable types from the "Model Specification" category, we find that the disagreement among the primary studies could be greatly reduced if they had (i) included a square term of temperature to model the nonlinear effect of warming (see variable 2 in Table 1), (ii) used a growing season temperature measure (see variable 3 in Table 1), and (iii) were based on cross-sectional data (see variable 4 in Table 1). The importance of these study characteristics are supported by previous findings in the literature that (i) temperature has a nonlinear effect on agriculture (Schlenker and Roberts 2009), (ii) crops are affected almost exclusively by temperature during their growing seasons, and (iii) farmer's adaptations to warming are captured by cross-sectional data (Mendelsohn, Nordhaus, and Shaw 1994).

Figure 3 demonstrates what would have had happened if the primary studies had included the three abovementioned study characteristics. Compared with Figure 2, Figure 3 shows that primary studies that have these three characteristics have substantially less disparity, and

[10] In meta-analysis, the sub-category regression is usually used to identify the contribution of each category on explaining the inconsistency among primary studies (Loomis and White 1996, Nelson and Kennedy 2009).

have findings about warming that are generally consistent with the simulation based literature (Rosenzweig and Parry 1994, Challinor et al. 2014). For example, 85.7% of the studies in the *Low* latitude group with these characteristics estimated negative and statistically significant effects of warming, while all the studies in *High* latitude group estimated positive and statistically significant effects.

[Figure 3]

5. Conclusion

Having a good understanding of the relationship between global warming and agricultural production can help policy makers to better anticipate issues concerning food security. However, although there is a growing econometric literature on this topic, there is also much disagreement on what the effect of warming is, in particular, whether it is positive or negative, or if there is an effect at all.

Using a standard meta-analysis, this article identifies the sources of this disagreement using the estimates of the effect of warming on agricultural output from 130 primary studies. Our meta-regression results show that differences in where the primary study is based on, the crops studied, and the biases in publication can explain why the primary estimates differ. Importantly, much of this disagreement also comes from differences in model specification. We find that if the primary studies had modelled temperature nonlinearly, used a growing season temperature measure, and were based on cross-sectional data – characteristics that are supported by the literature – much of the disagreement among them would go away. In addition, when these three characteristics are included, the estimated results on warming would be consistent with those from simulation based studies, which found that warming will lead to positive yield changes in the high latitudes while causing damages in the low latitudes.

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Figure 1: Geographic distribution of the observations

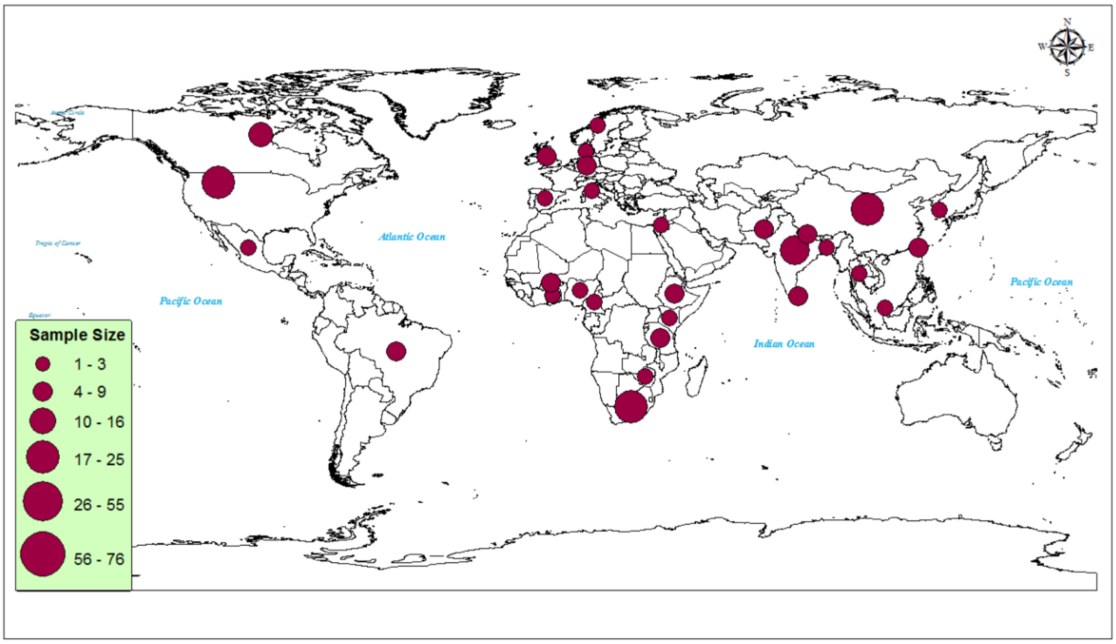
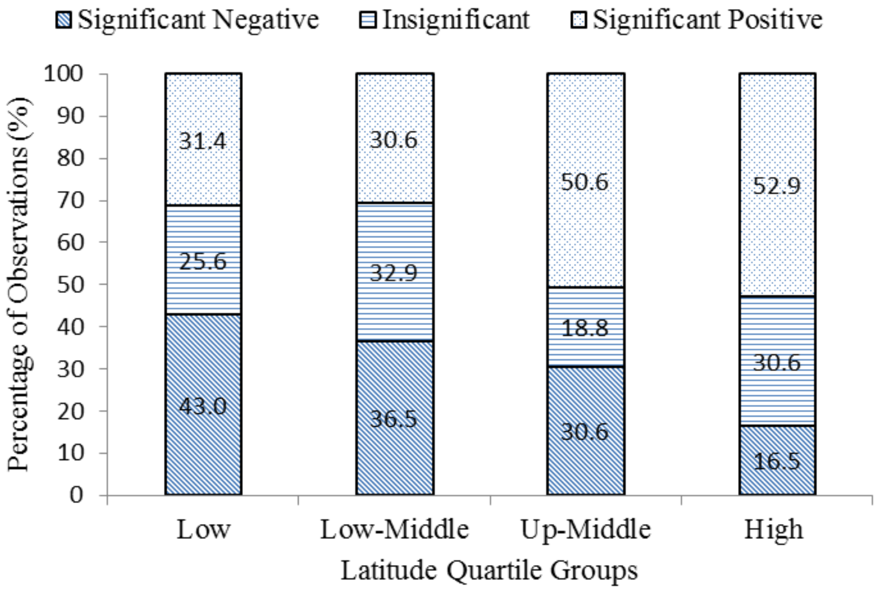


Figure 2 Distribution of the meta-dependent variable within each latitude quartile group



Note: This figure shows the percentage of observations reporting (i) positive and significant effects of warming, (ii) insignificant effects, (iii) negative and significant effects (all at the 10% significance level) for each of the four sample latitude quartile group (refer to footnote 8).

Table 1: Definition of the meta-independent variables

Meta-independent variables	Definition
Model specification	
(1) *Measures of output*	Agricultural output is measured by profits or quantity (1 = Profits , 0 = Quantity)
(2) *Non-linear setting*	Including a square term of temperature in the regression (1 = Yes, 0 = No)
(3) *Temperature measures*	Using a yearly temperature measure or a growing season temperature measure.† (1 = Yearly measure, 0 = Growing season measure)
(3) *Data types*	Uses cross-sectional data or panel data (1 = Cross-sectional data, 0 = Panel data)
(5) *Control precipitation*	The primary regression controls precipitation (1 = Yes, 0 = No)
(6) *Control irrigation*	The study sample is from irrigated land or rain-fed land (1 =Irrigated land, 0 = Rain-fed land)
Regional differences	
(7) *Latitude*	Mean latitude of the study area (Degree)
Publication bias	
(8) *Publication status*	Published (in journal or book) or not (1 = Yes, 0 = No)
(9) *Research time*	Year of study (Year)
Biological differences	
(10) C*rop types*	Maize, soybean, wheat, rice or land value (0 = Land value, 1 = Maize, 2 = Soybean, 3 = Wheat, 4 = Rice)#

†: the yearly temperature measure includes yearly mean temperature and yearly degree-day; the growing season temperature measure contains growing season mean temperature and growing season degree-day.

#: Maize, soybean, wheat and rice are the most frequently studied crops. There are also lots of econometric studies examined the effect of warming on farmland values, which reflects the effect of warming on the combination of various crops.

Table 2 Summary statistics of the meta-independent variables

Panel A: Continuous variables	Mean	Standard Deviation	Min	Max
Latitude (Degrees)	30.07	14.80	0.005	64.32
Research time (Year)	2010	4	1992	2014

Panel B: Discrete variables	Variable = 1	Variable = 0
Measure of output (1 = Profits, 0 = Quantity)	145	196
Non-linear setting (1 = Yes, 0 = No)	207	134
Temperature measures (1 = Yearly measure, 0 = Growing season measure)	232	109
Date type (1 = Cross-sectional, 0 = Panel)	148	193
Control precipitation (1 = Yes, 0 = No)	311	30
Control irrigation (1 = Yes, 0 = No)	41	300
Publication status (1 = Published, 0 = Unpublished)	235	106
Maize (1 = Yes, 0 = No)	70	271
Soybean (1 = Yes, 0 = No)	23	318
Wheat (1 = Yes, 0 = No)	42	299
Rice (1 = Yes, 0 = No)	53	287
Land value (1 = Yes, 0 = No)	152	189
Number of observations	341	

Note: the definition of meta-independent variables can be found in Table 1.

Table 3 The influence of the study characteristics on the estimated effects of warming (% of observations)

Variable	Variable Characteristic	Significant Negative Effect	Significant Positive Effect	Insignificant Effect
Measure of output	Value	35.9	44.1	20.0
	Quantity	28.6	**39.3**	32.1
Non-linear setting	With	27.0	53.6	19.3
	Without	38.8	22.4	38.8
Temperature measures	Yearly measure	31.5	37.9	30.6
	Growing season measure	32.0	48.6	19.0
Date types	Cross-sectional	33.0	49.3	17.6
	Panel	30.6	35.2	34.0
Control Precipitation	Control	33.8	43.4	22.8
	Not control	10.0	20.0	70.0
Control irrigation	*Irrigated land*	*26.8*	*46.3*	*26.8*
	Rain fed land	*32.3*	*40.7*	*27.0*
Publication status	Published	36.2	33.2	30.6
	Unpublished	21.7	59.4	18.9
Crops	Maize	27.0	41.4	31.4
	Soybean	4.4	78.3	17.4
	Wheat	40.5	26.2	33.3
	Rice	27.8	22.2	50.0
	Land value	36.8	46.7	16.5

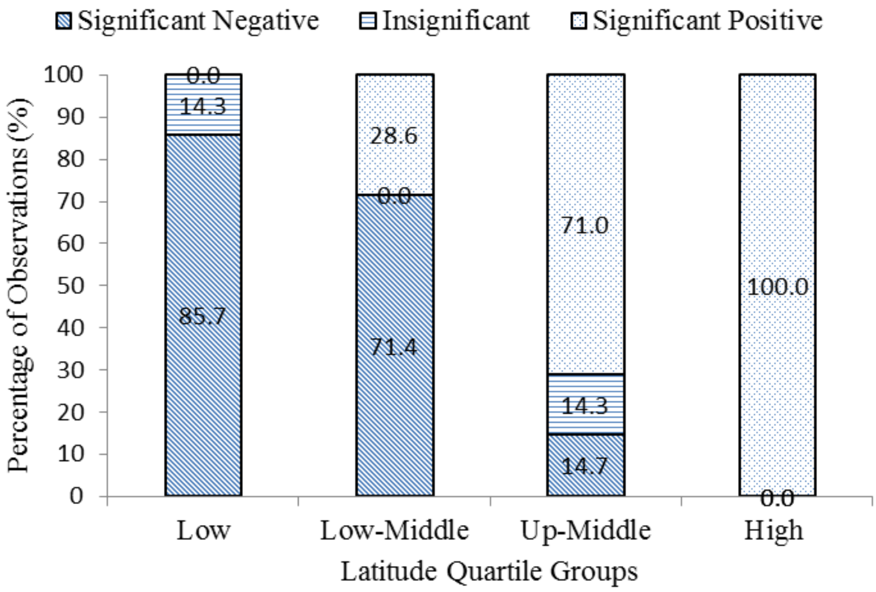
Note: The entries above numbers are the percentage of observations that reported significant negative, significant positive or insignificant effect of warming (all at the 10% significance level) associated with each study characteristic. All entries are calculated for the 341 observations. The definition of moderator variable is in Table 1.

Table 4 The influence of primary study characteristics on the inconsistency of the estimated effects of warming

Meta-independent variable	**(1) Full Model**	**(2) Exclude China**	**(3) Exclude Africa**	**(4) Exclude the United States**
Model specification				
Measures of output	0.47***	0.38**	0.97***	0.34**
(1 = Profits , 0 = Quantity)	(0.14)	(0.15)	(0.26)	(0.17)
Non-linear setting	0.58***	0.50***	0.62***	0.78***
(1 = Yes, 0 = No)	(0.11)	(0.13)	(0.12)	(0.16)
Temperature measures (1 =	0.54***	0.59***	0.45***	0.50***
Yearly, 0 = Growing season)	(0.10)	(0.12)	(0.11)	(0.14)
Data types	0.29*	0.49***	0.57***	0.25
(1 = Cross-sectional, 0 = Panel)	(0.15)	(0.17)	(0.20)	(0.18)
Control for precipitation	0.06	0.07	0.05	0.07
(1 = Yes, 0 = No)	(0.15)	(0.25)	(0.16)	(0.18)
Control for irrigation	-0.07	-0.20	-0.15	0.27
(1 = Yes, 0 = No)	(0.15)	(0.19)	(0.17)	(0.25)
Regional differences				
Latitude (Degree)	0.03***	0.03***	0.02***	0.02***
	(0.00)	(0.00)	(0.01)	(0.00)
Publication bias				
Research time	0.03**	0.03*	0.04***	0.02
(Year)	(0.01)	(0.01)	(0.01)	(0.02)
Publication status	-0.77***	-0.98***	-0.68***	-0.55***
(1 = Yes, 0 = No)	(0.10)	(0.12)	(0.12)	(0.13)
Biological differences				
Maize	0.45***	0.55***	0.31	0.59***
(1 = Yes, 0 = No)	(0.14)	(0.18)	(0.21)	(0.19)
Soybean	0.84***	0.97***	0.65***	1.01***
(1 = Yes, 0 = No)	(0.17)	(0.21)	(0.23)	(0.23)
Rice	0.68***	0.96***	0.50**	0.81***
(1 = Yes, 0 = No)	(0.18)	(0.25)	(0.23)	(0.22)
Wheat	0.24	0.50**	0.04	0.43**
(1 = Yes, 0 = No)	(0.16)	(0.20)	(0.22)	(0.21)
Land value	*Omitted*	*Omitted*	*Omitted*	*Omitted*
(1 = Yes, 0 = No)				
Constant	-63.58***	-52.16*	-71.79***	-34.01
	(24.24)	(27.69)	(26.66)	(37.10)
Observations	341	270	251	265
Adjusted R^2	64.89%	66.87%	62.85%	56.15%

Notes: The Huber-White heteroskedastic consistent standard errors are reported in parentheses. Significance levels are *** p<0.01, ** p<0.05, * p<0.1. The definition of moderator variable is in Table 1.

Figure 3: Distributions of the effects of warming within each latitude quartile groups for studies that satisfy our proposed model setting



Note: This figure shows the percentage of observations reporting (i) positive and significant effects of warming, (ii) insignificant effects, (iii) negative and significant effects (all at the 10% significance level) for each of the four sample latitude quartile group (refer to footnote 15).