The Impacts of Climate Change on U.S. Agriculture: Accounting for Omitted Spatial Dependence in the Hedonic Approach

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Abstract

This paper proposes a hedonic approach for estimating the impacts of climate change on agriculture that is robust to spatially-dependent omitted variables. I exploit the fact that certain estimators amplify the influence of such confounders to varying degrees, to detect the sign and magnitude of the bias and correct for it. Results suggest that large impacts of climate change on US agriculture are unlikely, in contrast to the large damages found in the literature. Previous findings appear biased downward severalfold, possibly due to the omitted differential rise of development pressure on farmland, which is correlated with climate. Results stand to various robustness checks. (JEL Q15, Q51, Q54, R14)

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There is a growing consensus that climate change is the global environmental challenge of our era, and there is a pressing need for reliable approaches of estimating its potential economic impacts. Agriculture has received unparalleled attention in this literature due to its reliance on climate and its central role in global development (Schelling, 1992). The past two decades have witnessed a lively debate, mainly centered on the US, over how to account for farmer adaptation to climate based on observational data. Despite methodological improvements, a fundamental disagreement persists regarding the sign of the potential effect of climate change on US agriculture (see Fisher et al., 2012 and Deschênes and Greenstone, 2012).

The identification of climate effects has become the forefront challenge in the quest to curtail biases from omitted variables. This paper contributes to this literature by introducing a hedonic approach that is robust to biases from spatially-dependent omitted variables, which are, in all likelihood, the dominant class of omitted variables in our context. The approach exploits the fact that certain estimators amplify bias from spatially-dependent confounders to varying and known degrees. I am therefore able to infer the sign and magnitude of bias in the hedonic regression and to correct for it. My results indicate that large positive or negative impacts of climate change on US agriculture are unlikely, contrasting large damages found in hedonic studies in the literature.

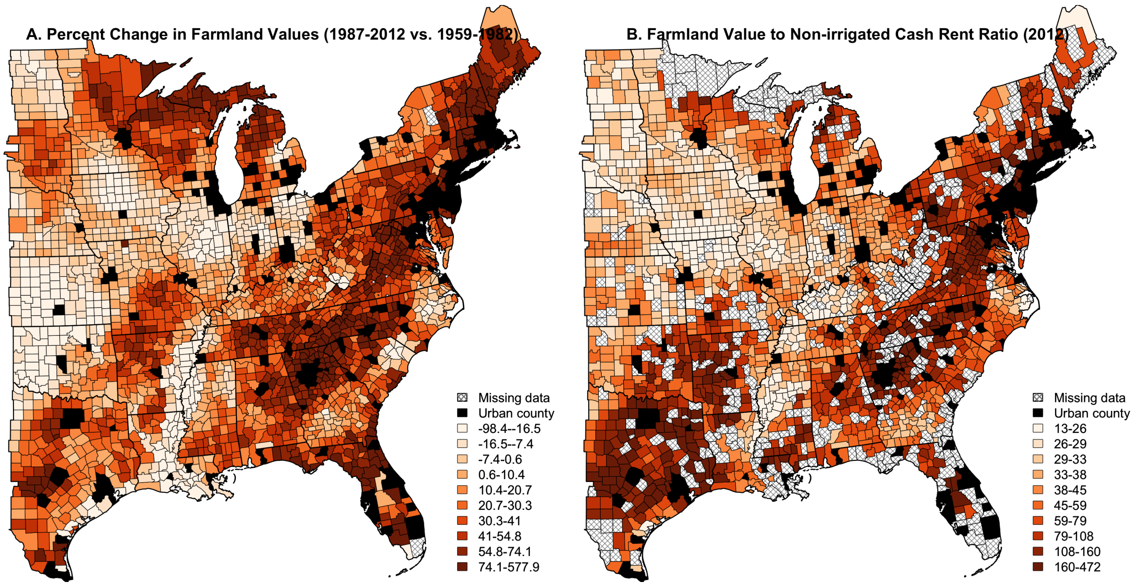
Mendelsohn et al. (1994, henceforth MNS) introduced the so-called "Ricardian" approach, an innovative hedonic method to estimate the economic impacts of climate change on the sector. Because farmers have adopted the most beneficial practices under a given climate, farmland value should reflect the full range of adaptations to that climate. The approach estimates agriculture's sensitivity to climate from the cross-sectional county-level variation of farmland values and current climate. These estimates are subsequently used for climate change impact projections based on current market conditions. MNS finds insignificant impacts of climate change on the sector but Schlenker et al. (2005, henceforth SHFa) finds large damages when non-irrigated counties are allowed to respond differently to irrigated ones in the hedonic regression. Schlenker et al. (2006, henceforth SHFb) finds similar results in a comprehensive hedonic study.

The cross-sectional nature of the hedonic approach makes it particularly vulnerable to omitted variables. Factors such as soil quality and the option value of farmland can introduce biases in unknown directions. This concern prompted Deschênes and Greenstone (2007, henceforth DG) to develop an alternative "profit" panel approach to control for time-invariant unobservables and estimate the sector's short-run sensitivity to random weather shocks. This approach estimates the effect of climate on a restricted profit function, so it does not allow for the full range of farmer adaptations to climate. Because DG find a small effect, it is interpreted as a potentially positive impact of climate change on long-run sector profits. However, Fisher et al. (2012) find that data errors and the smoothing of farmer income to weather shocks bias the DG results toward nullity. Deschênes and Greenstone (2012) acknowledge these concerns but propose an alternative distributed lag panel model to control for the smoothing effect of farm inventories. While negative, the revised DG impacts are substantially smaller than those based on the hedonic approach, which is puzzling. Impact projections from the hedonic approach, which allows for a greater range of adaptations, should be more optimistic.

The hedonic approach remains conceptually appealing but its empirical shortcomings and the likely presence of unknown omitted variables cast doubts on its reliability. Inquiring into long-term trends in farmland markets of the eastern US provides preliminary insights into how pervasive omitted variables could be.[1] Panel A in figure 1 shows that farmland appreciation over the past half century has followed a distinctive diffuse spatial pattern, which is correlated with climate.[2] Farmland values have increased more along the Northeast corridor, the Appalachian mountains and certain parts of the South, than over core agricultural areas such as the Corn Belt, the Mississippi Delta or the

[1] I follow SHFb and restrict the sample to counties located east of the 100th meridian west to avoid the confounding effect of irrigation.

[2] A crude OLS regression of the log farmland value change on climate variables yields statistically significant coefficients (F-statistic$= 117.8$, p-value$< 10^{-16}$) and an adjusted R^2 of 0.511. Climate variables are based on MNS and include linear and quadratic terms for the mean temperature and precipitation for January, April, July and October.



Notes: Urban counties are defined as having population densities exceeding 400 inhabitants per square mile. The color scale corresponds to deciles. Data sources are indicated in section III.

Figure 1: Farmland Market Indicators in the Eastern United States

Central and Southern Plains.

To explore the possible origin of this phenomenon, I map the ratio of farmland value to cropland cash rent in panel B of figure 1. This ratio is a common indicator of non-farm pressure on the farmland market, with high values indicating a higher option value of farmland for non-agricultural use. High-ratio areas are diffusely located around various booming areas of the East, and coincide with areas of greatest farmland appreciations.[3] More importantly, these appreciations have altered the cross-section of farmland values over time. For the 1959-1982 period, current low-ratio and high-ratio counties had an average farmland value of $2,345 and $1,909 per acre, respectively (2012$). The corresponding farmland values for the 1987-2012 period reach $2,276 and $2,638 per acre, respectively. This inversion indicates that the influence of non-

[3] I define high (low)-ratio counties as having a value-to-cash rent ratio above (below) 42.8, which is the median ratio for the 1,790 counties without missing observations. This excludes "urban" counties with population densities exceeding 400 inhabitants per square mile in 2012.

agricultural factors on recent farmland values is pervasive and affects areas well beyond direct proximity to urban counties.[4]

Because the option value of farmland strongly influences farmland values and appears correlated with climate, it could operate as an omitted variable in the hedonic model. Moreover, this potential omitted variable is likely to exhibit spatial dependence, making it particularly problematic. Pace and LeSage (2010) show that in such cases omitted variable bias is amplified in least squares estimation when the explanatory variables are also spatially dependent. This amplification affects other estimators used in this literature that solely account for the spatial correlation of disturbances. The bias amplification can be severalfold depending on the magnitude of the spatial correlation of regressors and omitted variables.

More generally, other potential omitted variables that have been explicitly proposed in this literature, such as soil quality, are also likely to exhibit spatial dependence. As an indication, *all* control variables used in previous implementations of the hedonic model, as well as disturbances, exhibit strong degrees of spatial dependence. This suggests that, in our context with spatially smooth climate variables, the presence of omitted variables is particularly worrying because any potential bias is likely amplified.

This paper proposes a hedonic approach that is robust to spatially-dependent omitted variables. I motivate the approach theoretically by deriving an order of vulnerability of three different estimators to such confounders. These include Ordinary Least Squares (OLS), the Spatial Error Model (SEM) and the Spatial Durbin Model (SDM). OLS is close to the Weighted Least Squares (WLS) estimator used in MNS and SHFa and the SEM is used in SHFb. To my knowledge, the SDM has not yet been used in this literature. This model

[4] The literature has well documented the sizable influence of urban growth on farmland markets (see Capozza and Helsley, 1989; Plantinga et al., 2002). However, the influence of low-density housing development, exurban growth and commercial development in rural areas along major highways is less well studied but is also found to be substantial (see Heimlich and Anderson, 2001 and Borchers et al., 2014). In addition, the pattern of farmland appreciation in figure 1 has a striking resemblance to the increase of median housing prices over a similar time period (not shown), highlighting a link between farmland and housing markets.

augments the classical linear model with an endogenous spatial lag of the dependent variable and spatial lags of explanatory variables. In the absence of omitted variables, all estimators are consistent but differ in efficiency. They would therefore yield similar climate change impact projections but different confidence intervals. However, the presence of an omitted variable would lead to predictable divergences in estimation. In our context, I find that OLS and SEM would amplify bias by a factor of 3.3 and 2.3-3.0, respectively. On the other hand, the SDM has a "neutral" bias amplification of 1. Because the SDM nests estimators previously considered in the literature, the SDM is consistent when other models are correctly specified, but the converse is not true. Moreover, restrictions among alternative models are testable.

I then estimate the hedonic model based on these three estimators and find substantial differences in climate change impacts. The differences in estimated parameters are statistically significant, confirming the presence of spatially dependent omitted variables. I find that estimators with greater bias amplification point to greater climate change damages, which indicates the direction of the bias in the hedonic regression must be downward. I also find that the relative magnitude of estimated impacts closely matches the relative bias amplification among estimators. This indicates estimated climate change damages mostly reflect the influence of omitted variables. I confirm this finding with a bias-corrected SDM estimator that points to statistically insignificant climate change impacts on the sector. Under the most severe climate change scenario, I find the preferred model in SHFb points to a significant yearly profit loss of $36.1 billion toward the end of the century, while the preferred model in this paper points to a statistically insignificant yearly profit gain of $1.4 billion. Various direct tests conclusively indicate the preferred model fits better the data than alternative models and results appear more stable over time and across specifications. Various robustness checks support these findings.

The remainder of the paper is structured as follows. In section I. I discuss the treatment of omitted variables in this literature and discuss my contribution. In section II. I show how alternative estimators amplify bias from spatially-dependent omitted variables to varying degrees. I then devote section III. to data sources and summary statistics. Section IV. presents the results based on alternative econometric models and section V. concludes.

I. Omitted Variables in the Climate Change Impact Literature

In a seminal study, MNS introduced the hedonic method to estimate the economic impacts of climate change on agriculture. The approach posits that the current climate, an exogenous input to the sector, should be capitalized in the value of farmland. The cross-sectional variation of farmland prices across the climate spectrum, the reasoning goes, can be used to identify the sector's sensitivity to climate under current market and technological conditions.

MNS recognizes that the presence of omitted confounding factors could bias climatic parameters and result in unreliable climate change impact projections. The solution in MNS primarily consists in controlling for some of these factors directly, via economic, regional and soil quality variables in a WLS estimation.[5] MNS also assess the presence of omitted variables indirectly, by analyzing the stability of impact projections for the 1978 and 1982 cross-sections. Because climate normals change slowly over time, the instability of impact projections indicates a changing correlation of omitted and climate variables, which confirms the presence of an omitted variable. However, this check would not rule out time-invariant or slowly-varying omitted variables, especially when a small number of consecutive cross-sections are considered. Based on this approach, MNS find little evidence that climate change would detrimentally affect US agriculture, countering earlier negative findings based on biophysical models (Adams, 1989; Adams et al., 1990; Kaiser et al., 1993; Adams et al., 1995).

The hedonic approach has generated considerable interest and criticism

[5]In terms of the econometric model, MNS weight their least squares model by either revenues per acre or total farmland, which assumes independence of observations. Economic controls include income per capita and population density (linear and quadratic terms). Regional controls include latitude and altitude while soil quality variables include salinity, presence of flood-prone zones, presence of wetlands, soil erosion, slope length, soil content in sand and clay, soil moisture capacity and permeability.

(see Cline, 1996; Kaufmann, 1998; Darwin, 1999; Quiggin and Horowitz, 1999). SHFa addresses several concerns in an important refinement that allows irrigated and non-irrigated counties to respond differently to climate. This study restricts the sample to non-irrigated counties, which are mostly located in the East, and find large negative impacts on the sector.[6] SHFa conclude that irrigation is confounded with climate and should not be treated as an additional control but as a feature affecting all slopes in the hedonic regression.[7] In a closely related hedonic study, SHFb confirm this result and introduce new climate variables and controls that improve model fit.[8] More importantly, SHFb find that results are robust to the introduction of state fixed-effects for the cross-sections considered.[9] This suggests that, even within states, warmer counties tend to have lower farmland values after controlling for other factors.[10] Finally, SHFb model the spatial dependence of disturbances with a Spatial Error Model (SEM) estimated via Generalized Methods of Moments (GMM) which yields more efficient estimates and corrected standard errors (Kelejian and Prucha, 1999). This innovation, while useful, still assumes explanatory variables are uncorrelated with disturbances.

To circumvent the shortcomings of the cross-sectional nature of the hedonic approach, DG develop an alternative "profit" panel approach to control for time-invariant unobservables. DG exploit random year-to-year weather fluctuations and their effect on farmer net revenue to identify the sector's short-run sensitivity to climate.[11] This approach provides an upper (lower) bound on damages (benefits) and DG's statistically insignificant result is interpreted as

[6]SHFa define rainfed counties as having less than 20 percent of the harvested cropland irrigated. SHFa find annual impacts of -\$5.32 billion (in 1982\$, or -\$12.66 billion in 2012\$) under the uniform warming scenario considered in MNS.

[7]SHFa considers the 1982, 1987, 1992, 1997 and 2002 farmland value cross-sections.

[8]This study uses the 100th meridian west as the threshold for rainfed/irrigated agriculture, instead of the percent of irrigated cropland used in SHFa. I adopt this delimitation in this study.

[9]SHFb considers the 1982, 1987, 1992 and 1997 farmland value cross-sections.

[10]An interesting finding in SHFb is that impacts are mostly driven by a single variable, namely the square root of degree-days above 34°C.

[11]DG compute net revenue or "profit" as the county-level total sales minus total production expenses divided by farmland acreage. The study uses data from the 1987, 1992, 1997, and 2002 Census of Agriculture.

a potentially positive effect of climate change on the sector. However, Fisher et al. (2012) find data errors in DG and replicate the results with corrected data to find significant negative impacts. These authors also argue that farmers use inventories to smooth the effect of year-to-year weather fluctuations on net revenue, further biasing the effect of these weather shocks toward zero. In other words, this approach is in turn vulnerable to attenuation from *time-varying* omitted variables.

In a noteworthy reply, Deschênes and Greenstone (2012) acknowledge the data issues in DG but highlight that the corrected estimated damage, although still negative, is less than half the damage suggested by the hedonic approach (SHFa and SHFb). Moreover, they propose to address the income smoothing of farmers with a distributed lag panel model. They find that climate change impact projections become mostly insignificant. These findings are puzzling because results from the hedonic approach, which allows for the full range of farmer adaptations, should be more optimistic than those from the "profit" panel approach, which only allows a restricted range of within-year adjustments in production practices.

The hedonic approach remains conceptually appealing because it captures a wide range of farmer adaptations and is simple to implement. However, its vulnerability to omitted variable bias seems difficult to circumvent. As previously discussed, recent farmland values seem significantly influenced by non-agricultural factors that are correlated with current climate. The omission of these factors could bias results. If one attempts to account for these factors explicitly, appropriate control variables would need to capture the dynamic aspects of the demand for land (Plantinga et al., 2002), the supply-side effects of scarce developable land (Saiz, 2010) or the effect of land use regulations (Brueckner, 1990).[12]

And yet, controlling for all these factors may prove insufficient because other omitted variables are plausible. However, confounding factors in our

[12] A complicating factor, is that farmers expectations about future land use conversions are affected by farmland fragmentation and the spatial pattern of housing development within counties and neighboring areas in ways that are difficult to observe (Heimlich and Anderson, 2001).

context belong, in all likelihood, to a spatial class. Indeed, suspect variables such as the option value of farmland or unknown soil characteristics, can be reasonably expected to exhibit spatial dependence. For instance, the ratio of farmland value to cash rent shown in panel B of figure 1 is spatially autocorrelated, just as are *all* control variables used in this and previous studies. Therefore, an effective solution should strive to accommodate unknown spatially omitted variables in the hedonic model.

Observational cross-sectional models appear inherently vulnerable to omitted variables. However, some cross-sectional estimators are more vulnerable than others to spatially-dependent omitted variables. In this study, I exploit the known and varying sensitivity of three different estimators to spatial confounders to detect the sign and magnitude of bias in the hedonic regression.

Theoretically, I find that OLS and SEM amplify bias from spatially dependent omitted variables by a factor of 3.3 and 2.3-3.0, respectively. On the other hand, the SDM has a "neutral" bias amplification of 1. This latter model eliminates the amplifying effect of spatially dependent confounders. In the absence of spatially dependent confounders, the three estimators should yield similar parameter estimates and therefore similar climate change impact projections. However, the presence of spatially-dependent confounders lead to divergence of parameter estimates and therefore to divergence of climate change impact projections. Moreover, one can infer the direction of the bias from the order of climate change impact projections based on these estimators. If climate change impacts projections are increasingly optimistic (pessimistic) for SDM, SEM and OLS one can infer the bias is upward (downward) and the true impacts are more negative (positive). Furthermore, it is possible to obtain bias-corrected SDM climate change impact projections, which makes the proposed approach robust to spatially-dependent omitted variables.

I then explore the hedonic model empirically based on these estimators. I rely on a long series of cross-sections spanning 1950-2012. To my knowledge, this is the longest-spanning exploration of the hedonic approach for climate change analysis. First, I find that OLS and SEM estimates do not exhibit stable results over this longer sequence of cross-sections, no matter what climate variable specification is used. On the other hand, SDM projections are more stable across time and specifications. Second, I test directly for omitted variables by contrasting OLS and SEM estimates, which should be statistically similar if spatially-dependent variables are absent. This indicates that impact projections based on these models are biased. Third, I find that climate change impact projections are increasingly detrimental for SDM, SEM and OLS. It naturally follows that the underlying omitted variable bias in US hedonic studies such as SHFa and SHFb must be downward, toward more negative effects.

The differences in climate change impact projections across estimators is substantial. Toward the end of the century under the most extreme scenario (RCP8.5), I find impacts of -87.2, -79.4, and -26.5% projected change in farmland values for the pooled OLS, pooled SEM and SDM, respectively.[13] Although the latter impact result is statistically insignificant, it corresponds to a model that is biased downward, although without amplification. A bias-corrected SDM impact projection for the same scenario points to a statistically insignificant impact of+2.6% change in farmland values. Climate change impact projections based on OLS and SEM are 3.3 and 3.0 times larger than the damage projection based on the SDM.[14] Interestingly, these impact ratios match very closely the theoretical predictions of bias amplification.

II. Model

A. Data Generating Process

In this section I illustrate how certain estimators have varying degrees of vulnerability to biases from spatially-dependent omitted variables and how to recovered bias-corrected estimates. As illustrated in figure 1, important omitted factors such as the option value of farmland do not follow state boundaries, but exhibit a spatially diffuse pattern. In other words, the omitted variable is

[13]OLS and SEM with state fixed-effects point to -79.3 and-69.0%, respectively.
[14]The ratio is 3.0 and 2.6 for OLS and SEM with state-fixed effects.

likely correlated in space, with values that are more similar among neighboring locations than among distant ones. This is in all likelihood the dominant class of omitted variable in our context. Indeed, all suspect variables and controls can be reasonably expected or shown to exhibit spatial dependence. For instance, the option value of farmland is likely to affect neighboring counties similarly due to the nature of development pressure. Also, neighboring counties tend to have similar soil characteristics due to the underlying spatial similarities in soil-forming factors (Jenny, 1994, p.27-28).

Let us assume the DGP underlying farmland values $\mathbf{y}$ takes the form $\mathbf{y} = \mathbf{X}\beta + \mathbf{e}$, where $\mathbf{X}$ is an $n \times k$ matrix of regressors including climate variables and other controls, and β is a vector of parameters. In our context, disturbances $\mathbf{e}$ are spatially correlated. This type of dependence is most commonly expressed as an autoregressive spatial process $\mathbf{e}= \rho\mathbf{We}+\epsilon_e$, where $\mathbf{W}$ is a spatial weight matrix, ρ a spatial autocorrelation parameter and ϵ_e is a well-behaved error term. The spatial weight matrix $\mathbf{W}$ is a spatial lag operator, performing weighted averages of neighboring observations.[15] The error in each location $\mathbf{e}$ is therefore partly determined by the average error of surrounding locations $\mathbf{We}$. This process yields spatially smooth disturbances.[16]

For illustrative purposes, let us define a simple omitted variable $\mathbf{Z} = \mathbf{X}\gamma + \epsilon_z$, where γ is a vector representing the strength of the relationship between $\mathbf{Z}$ and $\mathbf{X}$, and ϵ_z is a well-behaved error. The variance of ϵ_z governs the magnitude of the correlation between the explanatory and omitted variables. This corresponds to the familiar expression for a linearly-dependent omitted variable. I later discuss more general cases.

Introducing the omitted variable in the spatially dependent error yields $\mathbf{e} = \rho\mathbf{We} + \mathbf{X}\gamma + \epsilon$ where $\epsilon = \epsilon_e + \epsilon_z$. The omitted variable now also becomes spatially dependent. The value of the error at a given location now contains the

[15] It is common to assume that these weights sum to unity for each observation, in which case $\mathbf{W}$ is called "row-standardized". These weights can be binary (same weight for all neighbors) or a decreasing function of distance (e.g. inverse distance weights). Note that the diagonal elements of $\mathbf{W}$ are zero, so this operator does not perform a "window average" but a weighted average of *neighboring* observations only. Also ρ is bounded between -1 and 1, but is expected to be positive in our empirical application.

[16] Various versions of $\mathbf{W}$ are considered in the empirical application.

omitted variable in that location but also the weighted average of the omitted variable in neighboring locations. This feature, as I will show, exacerbates omitted variable bias in OLS and SEM when the $\mathbf{X}$s have a smooth spatial pattern, just as climate variables do. The model DGP can be rearranged in the following reduced-form where the random component is i.i.d:[17]

$$\mathbf{y} = \mathbf{X}\beta + (\mathbf{I}_n - \rho\mathbf{W})^{-1}(\mathbf{X}\gamma + \epsilon) \tag{1}$$

B. Bias in OLS

Previous hedonic models in this literature have been based on WLS (MNS, SHFa) or a SEM (SHFb). Here I illustrate how OLS is affected in the presence of an omitted variable in spatially correlated disturbances.[18] Under the DGP in (1) it can be shown that the expected value of the OLS estimator for β takes the following form:[19]

$$E[\hat{\beta}_{\mathbf{OLS}}] = \beta + [\underbrace{\mathbf{I}_k + \rho(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{I}_n + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + ...)\mathbf{X}}_{\mathbf{P_{OLS}}}]\gamma \tag{2}$$

This is a general expression representing omitted variable bias for OLS where $\mathbf{P_{OLS}}$ is a $k \times k$ matrix representing a bias amplification factor. $\mathbf{P_{OLS}}$ has a straightforward interpretation in a partitioned regression model (Greene, 2008, p.27). One can recognize that $\mathbf{P_{OLS}} = \mathbf{B}_0 + \rho\mathbf{B}_1 + \rho^2\mathbf{B}_2 + ...$, where $\mathbf{B}_0 = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X} = \mathbf{I}_k$, $\rho\mathbf{B}_1 = \rho(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{X}$, $\rho^2\mathbf{B}_2 = \rho^2(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}^2\mathbf{X}$, etc. Each of the columns of $\mathbf{P_{OLS}}$ consists of a weighted sum of the slopes of the least squares regression of $\mathbf{X}$ on the successive spatial lags of $\mathbf{X}$. This amplification factor can be computed from the data with a assumption on ρ.

[17]Previous studies have assumed special cases of this DGP.

[18]I explore OLS instead of WLS for simplicity. The bias for OLS is associated with its underlying assumption of independence of observations. This assumption also characterizes WLS, so results are analogous.

[19]Note that $(\mathbf{I}_n - \rho\mathbf{W})^{-1} = \mathbf{I}_n + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + ...$ where $\mathbf{W}^j$ is the jth order lag operator. For instance, $\mathbf{W}^2\mathbf{X} = \mathbf{W}(\mathbf{W}\mathbf{X})$ and note that $\mathbf{W}^0 = \mathbf{I}_k$. A more general and formal version of this result is provided in Pace and LeSage (2010), who explore the biases of least squares under alternative DGP.

It is useful to explore how (2) simplifies under various assumptions. Without spatial dependence in the disturbances we have $\rho = 0$ and $\mathbf{P_{OLS}} = \mathbf{I}_k$ and (2) simplifies to $E[\hat{\beta}_{\mathbf{OLS}}] = \beta + \gamma$. The bias amplification factor is neutral and corresponds to the familiar textbook expression for omitted variable bias with well-behaved disturbances. However, this study and previous research finds the error is positively and spatially correlated in the hedonic regression so $\rho > 0$. Another case is when $\rho > 0$, but $\mathbf{X}$ is orthogonal to its successive spatial lags $\mathbf{WX}$. This occurs when $\mathbf{X}$ has an uncorrelated or "noisy" spatial pattern. In this case $\mathbf{B}_0 = \mathbf{I}_k$, but the other $\mathbf{B}_j$ cancel out. This also yields $\mathbf{P_{OLS}} = \mathbf{I}_k$ with a neutral bias amplification. However, climate variables exhibit a smooth spatial pattern, so $\mathbf{X}$ is not orthogonal to its successive spatial lags $\mathbf{WX}$, $\mathbf{W}^2\mathbf{X}$, etc.[20] In this case $\mathbf{P_{OLS}}$ maintains its general form in (2) and the columns of $\mathbf{B}^0$, $\mathbf{B}^1$, $\mathbf{B}^2$, etc. are non-negative vectors. This shows that the amplification occurs when both the error and the regressors of interest are spatially correlated.

For clarity of exposition, I explore the simple case with $k = 1$. Here $\mathbf{P_{OLS}}$ becomes a scalar equal to $1 + \rho b_1 + \rho^2 b_2 + ...$, where b_j is the coefficient of the regression of $\mathbf{X}$ on the jth spatial lag of $\mathbf{X}$, $\mathbf{W}^j\mathbf{X}$. Because $\mathbf{X}$ is very similar to its spatial lags we expect $b_j \approx 1$.[21] Therefore $\mathbf{P_{OLS}}$ takes the approximate form of a geometric series, $\mathbf{P_{OLS}} \approx 1/(1-\rho)$. This results in a bias amplification that is non-linear with ρ. For instance, for $\rho = 0.3$, 0.5 and 0.7, the corresponding bias amplification factors are approximately 1.43, 2 and 3.33. In this and previous studies such as SHFb we have $\rho \approx 0.7$, so the bias amplification is severalfold. This means that a relatively weak omitted variable (small γ) could have a disproportionate effect on $\hat{\beta}_{\mathbf{OLS}}$ due to the combined spatial dependence of the error and the relevant regressors.[22]

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[20] The correlation between climate variables and their spatial lags exceed 0.95 for all variables considered.

[21] This is confirmed empirically. For the degree-days variable (8-32C, April-September) I obtain $b_1 = 1.006$ and $b_{10} = 1.027$.

[22] When $k > 1$, the off-diagonal elements of $\mathbf{P_{OLS}}$ correspond to the a weighted sum of the slopes of the least squares regression of one of the regressors in $\mathbf{X}$ on the successive spatial lags of the *other* regressors in $\mathbf{X}$. These off-diagonal elements are positive if the covariance among climate variables is positive. In this case, the bias amplification would be greater.

C. Bias in the SEM

To explore how the SEM is affected in this context, I find useful to express the model DGP as a reduced-form expression with a well-behaved error term. Pre-multiplying the DGP by $(\mathbf{I}_n - \rho\mathbf{W})$ and re-arranging yields:

$$\text{(3)} \qquad \mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\underbrace{(\beta+\gamma)}_{\phi} + \mathbf{W}\mathbf{X}\underbrace{(-\rho\beta)}_{\theta} + \epsilon$$

This corresponds to a model augmented with an endogenous spatial lag of the dependent variable $\mathbf{Wy}$ and the spatial lag of the explanatory variables $\mathbf{WX}$. However, the SEM assumes a DGP of the form $\mathbf{y} = \mathbf{X}\beta + \rho\mathbf{We} + \epsilon$, which can be re-written in the following reduced-form with an i.i.d. error $\mathbf{y} = \rho\mathbf{Wy} + \mathbf{X}\beta + \mathbf{WX}\beta/(-\rho) + \epsilon$. For the SEM to be specified correctly, this expression must match the model DGP in (3). This only occurs when $\phi = -\theta/\rho$. This is known as the common factor restriction. For it to hold, we *must* have $\gamma = \mathbf{0}_k$. In other words, the presence of an omitted variable creates a wedge between ϕ and $-\theta/\rho$ that leads to inconsistency in the SEM.[23]

The SEM estimator for β can be expressed as $\hat{\beta}_{\mathbf{SEM}} = \left(\mathbf{X}^{*\prime}\mathbf{X}^{*}\right)^{-1}\mathbf{X}^{*\prime}\mathbf{y}^{*}$ where $\mathbf{X}^* = \mathbf{X} - \rho\mathbf{WX}$ and $\mathbf{y}^* = \mathbf{y} - \rho\mathbf{Wy}$ are spatially "filtered" variables (see Anselin, 1988). After some manipulation under the assumed DGP we obtain:

$$\text{(4)} \qquad E[\hat{\beta}_{\mathbf{SEM}}] = \beta + [\underbrace{\mathbf{I}_k + \rho(\mathbf{X}^{*\prime}\mathbf{X}^{*})^{-1}\mathbf{X}^{*\prime}\mathbf{WX}}_{\mathbf{P_{SEM}}}]\gamma$$

$\mathbf{P_{SEM}}$ has an analogous interpretation to $\mathbf{P_{OLS}}$, although the former is a sum of only two terms. One can recognize that $\mathbf{P_{SEM}} = \mathbf{A}_0 + \rho\mathbf{A}_1$ where $\mathbf{A}_0 = (\mathbf{X}^{*\prime}\mathbf{X}^{*})^{-1}\mathbf{X}^{*\prime}\mathbf{X}^{*} = \mathbf{I}_k$ and $\rho\mathbf{A}_1 = \rho(\mathbf{X}^{*\prime}\mathbf{X}^{*})^{-1}\mathbf{X}^{*\prime}\mathbf{WX}$. Each of the columns of $\mathbf{P_{SEM}}$ consists of a weighted sum of the slopes of the least squares regression of $\mathbf{X}^*$on itself and on $\mathbf{WX}$.

Similarly, this expression simplifies under various assumptions. If disturbances were spatially independent $\rho = 0$, we get $\mathbf{P_{SEM}} = \mathbf{I}_k$ and (4) simplifies

[23] I am indebted to Professor James LeSage for pointing this out. Also, see LeSage and Pace (2009, p.158) for a discussion on this matter.

to $E[\hat{\beta}_{\mathbf{SEM}}] = \beta + \gamma$. The bias amplification is neutral. The next case corresponds to $\rho > 0$ and $\mathbf{X}$ is orthogonal to its first spatial lag $\mathbf{WX}$. This implies that $\mathbf{X}^*$ is also orthogonal to $\mathbf{WX}$, so $\mathbf{P_{SEM}} = \mathbf{I}_k$ and we obtain the same neutral result. However, this is not our context. In our case $\mathbf{P_{SEM}}$ should maintain its general form in (4) and the columns of $\mathbf{A}^0$ and $\mathbf{A}^1$ are non-negative vectors.

Again, it is useful to consider the case with $k = 1$ to draw some comparisons with OLS. In this case $\mathbf{P_{SEM}}$ becomes a scalar equal to $1 + \rho a_1$, where a_1 is the coefficient of the regression of $\mathbf{X}^*$ on the first spatial lag of $\mathbf{X}$, $\mathbf{WX}$. In appendix A0 I show that for $k = 1$, $P_{SEM} \approx (1-\rho)\sigma^2_X/\sigma^2_{X^*}$. This amplification factor can be computed for a given climate variable with an assumption on the value of ρ. I find that P_{SEM} is greater than 1 and increases with ρ. In this and previous studies such as SHFb we have $\rho \approx 0.7$ and a back-of-the-envelope calculation suggests an amplification factor for SEM in the range of $2.3-3.0$.[24] This is lower than the corresponding theoretical amplification for OLS of 3.33. Despite accounting for spatial correlation of the error, the SEM estimator also amplifies omitted variable bias, but to a lesser extent than OLS.

An interpretation of this results is that the bias in both OLS and SEM emerge from the omission of spatial spillovers of omitted variables correlated with at least a subset of the $\mathbf{X}$s. This could be captured by the inclusion of $\mathbf{WX}$ in the model. Because regressors in the SEM are spatially "filtered", its bias amplification is smaller than for OLS. Basically, the use of $\mathbf{X}^*$ as a regressor rather than $\mathbf{X}$ reduces the correlation between the regressor and the omitted variable. This insight is useful for diagnosing the direction of bias in the hedonic model. If there is bias, one can infer its direction by contrasting OLS and SEM estimates or impact projections. Indeed, the amplification factor is independent of the sign of γ. If climate change projections based on OLS are more (less) detrimental than for SEM, it follows that the bias is downward (upward), toward more detrimental (beneficial) impacts. However, if OLS and

[24]For assumed values of ρ of 0.3, 0.5 and 0.7 (spatial weight matrix described later on) I obtain SEM amplification factors of 1.36, 1.75, 2.34 for the precipitation variable (April-September), and amplification factors of 1.41, 1.94, 3.04 for the degree-days variable (8-32$^{\mathrm{o}}$C, April-September), respectively.

SEM estimates are similar, it is an indication that spatially-dependent omitted variables are not affecting the result.

D. Bias in the SDM

One can estimate a model matching the DGP shown in (3). This corresponds to the SDM which can be estimated via Maximum Likelihood (ML) (LeSage and Pace, 2009, p.46). An important feature of this model is that it nests the SEM. Therefore, rather than imposing this DGP, one can test the common factor restriction $\phi = -\theta/\rho$ via a likelihood ratio (LR) test. If this restriction cannot be rejected, then we should favor the SEM specification.

Before I proceed, it is important to highlight that SDM coefficients cannot be directly interpreted as partial derivatives of $\mathbf{y}$. This inconvenience stems from the presence of $\rho\mathbf{W}\mathbf{y}$ on the right-hand side.[25] LeSage (2008) and LeSage and Pace (2010) develop an approach to spatially partition the effect of $\mathbf{X}$ on $\mathbf{y}$ into average "direct" and "indirect" effects. Average direct effects have a familiar interpretation analogous to the marginalist interpretation of OLS and SEM coefficients. These represent the sample average effect of a change in an explanatory variable for a given observation on the dependent variable of the same observation. Indirect effects, on the other hand, capture spatial spillovers on the dependent variable of a given observation from changes in explanatory variables of its neighboring observations.[26] Note that indirect effects are restricted to equal zero in OLS and SEM. In other words, these estimators are special cases of the SDM.

[25]One can re-arrange the DGP in (3) as $\mathbf{y} = (\mathbf{I}_n - \rho\mathbf{W})^{-1}(\mathbf{X}\beta + \mathbf{W}\mathbf{X}\theta + \epsilon)$. It becomes apparent that the computation of the marginal effect of the kth regressor for the the ith observation $\partial E[\mathbf{y}_i]/\partial \mathbf{X}_{ik}$, involves the $(\mathbf{I}_n - \rho\mathbf{W})^{-1}$ matrix. As previously mentioned, this matrix is equal to $\mathbf{I}_n + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + ...$ Therefore, this calculation also involves the "own" effects that propagate back to i through high-order $\mathbf{W}$s. Indeed, unlike in time-series, the second-order neighbors (or greater) of i often include i itself.

[26]The distinction between coefficients and effects for SDM is important. There has been confusion in the literature regarding the interpretation of spatial models with lagged dependent variables. Researchers have found that coefficients are sensitive to changes in $\mathbf{W}$. However, as discussed in LeSage and Pace (2014), the direct and indirect effects, which are the relevant economic measures, are fairly robust to changes $\mathbf{W}$. This finding is also apparent in this paper.

The SDM estimator for ϕ converges to $\beta+\gamma$ so it yields an asymptotically biased estimate of β. Interestingly, this bias is constant and independent of ρ or the spatial dependence of $\mathbf{X}$. This is unlike OLS or SEM for which the bias is amplified by these factors. In other words, the SDM does not amplify bias from spatially-dependent omitted variables. In fact, it is the inclusion of $\mathbf{WX}$ on the right hand side of the model that removes the bias amplification. The inclusion of $\rho\mathbf{Wy}$, on the other hand, removes the spatial dependence of disturbances.[27]

Although the SDM is biased, we can recover a bias-corrected estimate of the structural parameter β in (3) from the reduced-form estimates of ρ, ϕ and θ by noting that $\beta = -\theta/\rho$. This is feasible, under the assumed model DGP, because $\hat{\rho}$ is not affected by the omitted variable.[28] In a Monte Carlo study, Lacombe and LeSage (2015) show that this procedure yields fairly precise estimates of the true effects.

Any bias-correction of $\hat{\beta}$ assumes a particular DGP. Here, I assume a linear dependence between $\mathbf{X}$ and $\mathbf{Z}$. However, the true relationship might be non-linear or exhibit a more complex correlation pattern. If the true relationship is non-linear, then the present treatment may be interpreted as a linear approximation of that relationship. In other words, it would fall short of appropriately capturing the correct nature of the relationship between between $\mathbf{X}$ and $\mathbf{Z}$. In such circumstances $\mathbf{WX}$ would not capture the omitted spatial spillovers and the estimates would remain more biased. However, this would also be the case for OLS and SEM, and these would be affected by an additional bias amplification factor.

On the other hand, the omitted variable $\mathbf{Z}$ may exhibit a more complex spatial correlation with $\mathbf{X}$. This could include omitted variables that are "regionally" but not "locally" correlated with the explanatory variables. I explore this idea in the appendix (A3) and I find that the structural parameter β is not identified with a more complex omitted variable. However, the generality of

[27] In the appendix I show results are similar when the spatial correlation of errors is modeled directly in the "random" part of the model.

[28] One can rely on the delta method to obtain measures of dispersion of $\hat{\beta}$ from the estimated variance-covariance matrix of the reduced-form estimator.

the result holds, with SDM remaining less biased than OLS and SEM. Therefore, a conservative approach is to rely on the non-corrected estimator $\hat{\phi}$. This estimator is biased in the presence of a spatially-dependent omitted variable and points to different estimates than OLS and SEM. However, in such cases the SDM is less biased than OLS or SEM. I therefore present empirical results for both the non-corrected and the bias-corrected SDM estimator.

The framework presented here highlights that the presence of a spatially dependent omitted variable can be at least partly accounted for through the inclusion of spatially-dependent controls. The SDM eliminates the amplifying effect of omitted variable bias that affects OLS and SEM. It is important to emphasize that the SDM is consistent but inefficient when the DGP is OLS or SEM and there are no spatially dependent omitted variables. Nevertheless, the SDM provides correct standard errors in such cases. This means that, if the climate change impact estimates are not affected by spatially-dependent omitted variables, then OLS, SEM and SDM should yield statistically similar results. On the contrary, if results differ, then SDM is a more robust model that subsumes OLS and SEM as special cases. Moreover, models can be compared directly through testing.

I should highlight that the proposed model is not a panacea for controlling any type of omitted variable in a cross-sectional setting (Gibbons and Overman, 2012). The identification of the SDM relies on the exogeneity of climate and its local variation in the neighborhood of each observation. This strategy is especially suited for omitted variables that are spatially dependent and exhibit "diffuse" spatial patterns. This corresponds to our case as discussed in section I.. Needless to say, the SDM will fail to reduce bias from an omitted variable that is *not* spatially dependent. But so will OLS and SEM, which are special cases of the SDM. However, such an omitted variable would not result in bias amplification in any of these models. In other words, any bias that affects the SDM will also affect OLS and SEM, but these latter two models amplify the bias when it stems from a spatially-dependent omitted variable. I therefore propose the adoption of this estimator for the hedonic model as a more robust alternative to unknown spatially dependent omitted variables.[29] I explore this question empirically in the remainder of the paper.

III. Data Sources and Summary Statistics

A. Data Sources

This study relies on four major types of data: agricultural, climate, soil quality and general socio-economic data. Table 1 provides a summary of key variables in the study and their source. A portion of the agricultural data was obtained directly from *Quick Stats,* the US Department of Agriculture's (USDA) online database. This database provides data from the US Census of Agriculture as well as from various national surveys, such as the Cash Rent Survey, all conducted by USDA. The Census provides county-level aggregates of data collected from all farms.[30] The dependent variable in the study, farmland value, is obtained from the Census by asking farmers their estimate of the current market value of their land and buildings. This variable naturally reflects the option value of farmland for non-agricultural uses. Unfortunately, *Quick Stats* only provides Census data since 1997 so older Census data since 1950 were obtained from Haines (2004). To the best of my knowledge, this is the first study to incorporate this historical Census data for the purpose of climate change impact analysis.

The primary climate data source is Schlenker and Roberts (2009), who provide a detailed daily gridded dataset for 1950-2005 based on the interpolation of daily weather station data and monthly gridded data from the PRISM Climate Group , which is USDA's official climatological data.[31] These and the underlying PRISM data have a spatial resolution of just 4 kilometers and

[29] A general motivation for the adoption of this model in empirical settings can be found in LeSage and Pace (2010); LeSage (2014).

[30] USDA defines a farm as an operation having sold more than $1,000 of agricultural products during the census year.

[31] Following Schlenker and Roberts (2009), I rely on the monthly precipitation variables from PRISM, rather than on re-aggregated daily precipitation interpolations which appear to be noisy.

Table 1: Variables and Data Sources

Variable(s)	Time Periods Used	Resolution	Source
Agriculture:			
Value of land and buildings, farmland area (Census)	1997, 2002, 2007, 2012	County	USDA *Quick Stats*
	1950, 1954, 1959, 1969, 1974, 1978, 1982, 1987, 1992	County	Haines (2004)
Non-irrigated cropland cash rent (Cash Rent Survey)	2009-2012	County	USDA *Quick Stats*
Climate:			
Daily minimum and maximum temperature	1950-2005	4 km	Schlenker and Roberts (2009)
Monthly average temperature and precipitation	1912-2005	4 km	PRISM
Cropland weights for grid-to-county aggregation	2008-2014	30 m	USDA CDL
Controls:			
Population	1970-2012	County	US Census
	1950, 1960	County	US Census via Haines (2004)
Personal income per capita	1969-2012	County	BEA
Family income	1949, 1959, 1969	County	US Census via Haines (2004)
Soil variables: average water capacity, clay content, minimum permeability, K-factor of topsoil, best soil class	N/A	Polygon, sub-county scale	USGS STATSGO

Notes: Only farmland values for 1964 were missing from Haines (2004) at the time of data collection.

cover the entire country. Because the data is gridded it needs to be aggregated to the county level to match the agricultural observations. I perform this aggregation by weighting each native PRISM grid by the amount of cropland it contains based on USDA's Cropland Data Layer (CDL).[32] Because I explore time periods prior to 1950, I also rely on the monthly temperature data from PRISM, which is available since 1895.[33]

The hedonic model relies on the cross-sectional variation of farmland values which are affected by known time-invariant factors such as certain soil quality characteristics. Soil quality data was obtained from the US Geological Survey's (USGS) STATSGO database which aggregates similar soils into distinct polygons across the country. Similar to climate data, county-level soil quality data is obtained by weighting each soil polygon by the amount of cropland based on the CDL.

The analysis also includes a set of economic control variables, namely county-level population density and income per capita. These controls have been introduced in an attempt to capture the influence of population pressures on farmland. County-level population data comes from the US Census and Intercensal Estimates. These data are only available online from the US Census for years 1970-2012. Prior census years were obtained from Haines (2004). Intercensal Estimates prior to 1970 were not readily available so I interpolate population between decennial censuses for each county using a natural spline.[34] Data on per capita personal income is obtained from the Bureau of Economic

[32]The CDL provides 30 meter resolution land cover pixels corresponding to over 100 classes. The weights were based on cropland pixel counts falling within each PRISM data grid. The average of CDL cropland counts for years 2008-2014 were used. In the appendix A1, I provide a map of the cropland weights as well as a table with all land cover classes that constitute cropland. Detailed crop cover data for older cross-sections (e.g. 1950) is not available. However, because farmland area has decreased by 27.4% from 1950 to 2012 and the most productive farmland has most likely remained in farms, cropland weights for recent periods can be thought as capturing the "core" agricultural area of each county for older time periods.

[33]Just recently, the PRISM group released daily data with 4 kilometer resolution free of charge. However, the earliest year is available is 1981.

[34]Just as with intercensal estimates, this approach is not meant to capture year-to-year fluctuations in population with precision, but provide an approximation of the population level between census years.

Analysis (BEA). Unfortunately, these only span the 1969-2012 period. I use family income from the US Census as a substitute for earlier time periods.[35] Similar to population, I interpolate family income between decennial censuses for each county using a natural spline.[36] All values in the paper are expressed in 2012 USD using the Consumer Price Index (CPI).[37]

B. Summary Statistics

Agricultural data. Summary statistics for farmland values are presented in table 2. Overall, farmland values have increased over the past several decades, with some areas experiencing disproportionally greater appreciations as illustrated in panel A of figure 1. Over this period, the farmland value cross-section has greatly changed. For instance, the correlation between (log) farmland values over 1950-2012 relative to the 1987-2012 average has fluctuated between 0.687 in 1950 and 0.972 in 1997.[38] The spatially heterogenous pattern of farmland appreciation has been coupled with a steady but equally heterogenous fall in total farmland area across the eastern part of the country. In 1950, land in farms across the sample totaled 688 million acres. By 2012, this acreage had dropped to 500 million, a 27.4% decrease. The number of urban counties has more than doubled over 1950-2012 but the number of counties classified

[35]Note these variables are not directly comparable because family size varies across the country. I therefore compare personal capital income and family income for 1969 which is the earliest overlapping year. The correlation is 0.82 for all US counties and 0.87 for counties in the eastern sample. There are a few outliers. Counties with relatively low family income relative to personal income per capita include places like New York county (NY) or small coastal counties such as Kenedy county (TX). Counties with relatively low personal income per capita relative to family income per capita include highly remote counties such as Hinsdale county (CO) where family size is likely to be large. Outliers do not tend to be highly agricultural in nature, so this variable seems appropriate.

[36]Again, this is not intended to capture short run fluctuations in income within counties, but to preserve the variation in income across counties.

[37]Other studies have used the GDP implicit price deflator. I use the CPI because it is available over a longer time span and these two indexes are virtually indistinguishable within their overlapping time period with a correlation of 0.997 over 1947-2012.

[38]The correlation of farmland value relative to 1987-2012 are 0.687 (for 1950), 0.715 (1954), 0.771 (1959), 0.810 (1969), 0.874 (1974), 0.840 (1978), 0.872 (1982), 0.948 (1987), 0.966 (1992) 0.972 (1997), 0.967 (2002), 0.966 (2007) and 0.934 (2012).

Table 2: Summary Statistics of Farmland Real Estate

Year(s)	Farmland Values (2012 USD)				Observations		
	μ	min	max	σ	*Non-urban*	*Urban*	*All*
1950	1,063	67	129,888	4,516	2,233	229	2,462
1954	1,283	68	297,803	7,071	2,233	229	2,462
1959	1,867	181	337,523	10,098	2,233	229	2,462
1969	2,324	244	772,776	16,351	2,227	225	2,452
1974	2,909	186	558,623	12,990	2,226	225	2,451
1978	3,632	440	224,056	6,412	2,227	226	2,453
1982	3,160	457	246,818	7,754	2,233	227	2,460
1987	2,439	362	321,491	7,817	2,223	226	2,449
1992	2,291	262	92,274	3,725	2,226	222	2,448
1997	2,795	280	346,299	9,419	2,234	227	2,461
2002	3,220	308	126,306	5,479	2,235	228	2,463
2007	3,989	497	147,550	6,254	2,236	227	2,463
2012	4,574	512	792,500	17,327	2,237	230	2,467
1959-1982	3,001	307	316,232	11,720	2,237	231	2,468
1987-2012	3,358	377	362,222	9,555	2,237	231	2,468

Notes: Data are for counties in the eastern sample multi-year averages ignore missing observations. Large changes in maximum values and standard deviations in consecutive sample years results from some highly populated counties being dropped from the Agricultural Census. This also drives changes in the standard deviation.

as non-urban remains large, exceeding 2,200 in all years. The analysis in this paper will be confined to these counties, following SHFb.

Climate data. I follow the literature and compute climate normals as the 30-year average of yearly weather. The main results in the paper follow the climate specification in SHFb, which includes linear and quadratic terms for degree-days between 8 and 32ºC and precipitation, the square root of degree-days exceeding 34ºC.[39] These variables are aggregated over the April-September period to reflect the growing season. I also report results for specifications based on monthly climate variables following MNS as well as linear

[39] Degree-days are computed using the double-sine method with a horizontal cutoff (see Ortiz-Bobea et al., 2015). The computations account for the time-path of temperature throughout the day.

Table 3: Summary Statistics of Climate Variables

Variable(s)		Month(s)	μ	min	max	σ
Degree-days	8-32ºC	Apr-Sep	2429.9	1108.3	3686.8	520.1
	10-30ºC	Apr-Sep	2058.8	848.8	3171.2	473.7
	>34ºC	Apr-Sep	9.5	0.0	140.2	13.7
	>30ºC	Apr-Sep	64.3	0.2	411.8	56.5
Precipitation (mm)		Apr-Sep	602.1	321.5	1041	97.6
		Jan	74.2	9.4	169.3	39.3
		Apr	89.6	20.1	149.2	21.9
		Jul	105.6	38.4	217.6	26.3
		Oct	81.2	31.9	135.7	18.5
Mean temperature (ºC)		Jan	0.0	-16.4	19.1	6.5
		Apr	12.9	2.5	24.2	4.3
		Jul	24.8	16.8	30.7	2.6
		Oct	13.9	4.9	26.0	4.0

Notes: The climatology window corresponds to 1976-2005. The sample comprises 2,470 counties in the eastern half of the US with at least some CDL cropland within their borders. Only 40 eastern counties did not satisfy this condition, most of them (36) correspond to incorporated cities in Virginia.

Table 4: Correlation of Climate Normals Over Time

Variable(s)		Month(s)	Correlation relative to 1976-2005						
			1916 -1945	1926 -1955	1936 -1965	1946 -1975	1956 -1985	1966 -1995	1976 -2005
Degree-days	8-32ºC	Apr-Sep	-	-	-	-	0.999	1.000	1
	10-30ºC	Apr-Sep	-	-	-	-	0.999	1.000	1
	>34ºC	Apr-Sep	-	-	-	-	0.991	0.997	1
	>30ºC	Apr-Sep	-	-	-	-	0.995	0.999	1
Precipitation (mm)		Apr-Sep	0.944	0.940	0.935	0.950	0.967	0.983	1
		Jan	0.949	0.904	0.936	0.942	0.986	0.993	1
		Apr	0.882	0.865	0.848	0.889	0.931	0.966	1
		Jul	0.838	0.877	0.920	0.930	0.954	0.981	1
		Oct	0.820	0.776	0.781	0.813	0.881	0.942	1
Mean temperature (ºC)		Jan	0.996	0.994	0.996	0.996	0.999	0.999	1
		Apr	0.997	0.997	0.998	0.998	0.999	1.000	1
		Jul	0.988	0.991	0.994	0.996	0.995	0.999	1
		Oct	0.997	0.997	0.996	0.997	0.998	1.000	1

Notes: Climate variables are county-level averages over the corresponding 30-year period. The data covers 2,470 counties lying east of the 100th meridian west. Mean temperature and precipitation are generated from the monthly gridded PRISM dataset while the degree-days variables were constructed from the daily gridded dataset in Schlenker and Roberts (2009).

linear degree-days variables.[40] Summary statistics for all climate variables (1976-2005) considered in the paper are presented in table 3. There is considerable climatic variation across the sample with a cross-sectional range of approximately 35ºC and 14ºC for mean temperatures for January and July, respectively. Large variations are also observed for degree-days variables. Precipitation also varies considerably across all months, although the variation is naturally smaller when precipitation totals for a longer time period such as April-September is considered.

Because I estimate hedonic models over a long period of time, it seems natural to verify how climate cross-sections have evolved. Table 4 shows the

[40]The specification in MNS includes monthly climate normals for mean temperature and precipitation for the months of January, April, July and October. The linear degree-days specification includes linear terms for degree-days between 10 and 30ºC, and degree-days above 30ºC.

correlation of climate normals over time. Because data from Schlenker and Roberts (2009) is only available since 1950, I cannot assess the correlations of degree-days variables for earlier time periods. However, the correlations in excess of 0.95 for most variables, especially for temperature, indicate the climate cross-section has not changed much. It would be interesting to explore regional trends in climate, and the resulting agricultural responses over such a long time period. However, the nature of the underlying PRISM data so far precludes from this type of analysis making detection vulnerable to artifacts.[41] I therefore rely on climate normals for the 1976-2005 for all regressions.[42] It is worth noting that the farmland value cross-section appears to have evolved much more than the climate cross-section as indicated by the lower and steadily decreasing correlations over time in the farmland value variable.

Climate change impacts are reported for various warming scenarios as projected by the Hadley GEM2-ES General Circulation Model (CGM) or HadGEM2-ES (Jones et al., 2011).[43] Starting in its fifth Assessment Report (AR5) in 2014, the Intergovernmental Panel on Climate Change (IPCC) adopted warming scenarios that correspond to Representative Concentration Pathways (RCP). Instead of emissions, these scenarios represent trajectories of greenhouse gas concentration. The scenarios are named based on the radiative forcing values in year 2100 relative to pre-industrial levels. The four scenarios are RCP2.6, RCP4.5, RCP6, and RCP8.5, corresponding to additional

[41] The PRISM group discourages the use of their data for trend detection. More specifically, the PRISM documentation states that the long-term average datasets *"are not currently suitable for calculating multi-decadal climate trends. Although longer-term networks are used, grids still contain non-climatic variations due to station equipment and location changes, stations openings and closings, and varying observation times."* (See p.5 in http://www.prism.oregonstate.edu/documents/PRISM_datasets.pdf, accessed 8/1/2015). In other words, although highly detailed, we ignore if statistically significant differences in PRISM cross-sections are driven by changes in climate or non-climatic factors.

[42] A possible robustness check could explore how results differ when the climate normals are computed based on the preceding 30-year weather average for each census year. Similar analysis in SHFb found no differences in the results when alternative climate cross-sections were used.

[43] Results based on other four GCM and the uniform warming scenario considered in MNS and SHFa are also available upon request. These are not presented due to space constraints but results are similar across GCM.

"trapped" atmospheric energy of 2.6, 4.5, 6.0, and 8.5 W/m^2, respectively. To put this in context, the RCP2.6 and RCP8.5 scenarios are likely to lead to *global* mean temperature increases of 1 and 2$^{\text{o}}$C by 2046-2065, respectively. Note that *regional* temperature changes can be much greater. I follow the approach outlined in Auffhammer et al. (2013) to generate county-level projections for mid-century (2036-2065) and end-of-century (2070-2099).[44]

Other data. Summary statistics for control variables are presented in table 5. The control variables in this study follow SHFb. Some controls overlap with those in MNS, but updated variables have greater explanatory power. As expected, income per capita and population density vary considerably across the sample, although the variation is substantially reduced when only non-urban counties are considered. For instance, the maximum income per capita drops from 119,000 to 83,600 USD. However, the mean income per capita remains fairly stable at around 37,000 USD. On the other hand, the mean population density drops significantly from over 250 to just under 80 inhabitants per square mile. In contrast, the distribution of soil quality controls does not seem to vary much when urban counties are excluded, indicating that the sample restriction is mainly removing the influence of highly populated and high income areas. The interested reader can find maps of all key climate and control variables in appendix A2.

IV. Results

A. Baseline Hedonic Model.

In this section I present regression results and climate change impact projections for a baseline hedonic model. I follow the preferred specification in

[44]First, I compute changes in monthly climate normals for each variable for mid-century (2036-2065) and end-of-century (2070-2099) periods relative to a historical reference period (1976-2005). Second, I downscale the relatively coarse projections on the GCM grid to the PRISM grid based on inverse distance weights between the four nearest GCM grid centroids to each PRISM grid. Third, I add the downscaled projections to the fine-scale climatologies of PRISM or Schlenker and Roberts (2009). This preserves the smoothness of climate variation in the projections. Fourth, I aggregate these projections to the county-level using cropland weights based on the 2008-2014 CDL as previously mentioned.

Table 5: Summary Statistics of Control Variables

Variables	All counties ($n = 2,469$)				Non-urban Counties ($n = 2,236$)			
	μ	min	max	σ	μ	min	max	σ
Income per capita (thousand 2012US$)*	37.13	17.92	119.35	8.92	36.17	17.92	83.63	8.08
Population density (pop/mi^2)*	260.4	0.3	70,922.5	1,895.9	77.3	0.3	398.6	81.7
Average water capacity (fraction)	0.146	0.070	0.275	0.027	0.147	0.070	0.225	0.027
Clay content (%)	27.1	3.1	61.6	9.4	27.5	3.1	58.3	9.0
Minimum permeability (µm/sec)	7.78	0.14	98.10	8.07	7.38	0.14	98.10	7.30
K-factor of topsoil (index)	0.30	0.10	0.48	0.07	0.30	0.10	0.48	0.07
Best soil class (fraction)	0.65	0.00	1.00	0.23	0.65	0.00	1.00	0.22
Latitude (^{o})	37.8	25.5	48.8	4.7	37.7	25.5	48.8	4.6

Notes: Variable descriptions: Average water capacity, measured in cm of water per cm of soil, is the volume of water available to plants when excess water in the soil has been drained. Clay content is an aspect of soil texture, which identifies the percent of soil composed of particles that have a diameter of less than 0.002 mm. Soil permeability or saturated hydraulic conductivity describes soil permeability by water and is measured in µm/s. The K-factor or soil erodibility is an index ranging from 0.02-0.69 that predicts vulnerability to soil erosion as a function of soil texture, organic matter content, and various aspects of soil structure. The best soil class variable refers to the proportion of soils within a county classified in the top three (I-III) of an eight-class index based on capability to produce commonly cultivated crops and pasture plants. (Sources: National Soil Survey Handbook, part 618 and 622.02).
*For clarity of exposition, income per capita and population density correspond to 2012 levels.

SHFb, which is a semi-log model of farmland values with degree-days climate variables and various controls. For comparison purposes, I present results based on OLS and a SEM estimated via GMM (Kelejian and Prucha, 1999). Due to space constraints, I only report regressions results based on averaged data for recent cross-sections (1987-2012). However, climate change impact projections are provided for all cross-sections. All spatial models in the main part of the paper are based on a queen contiguity matrix with row-standardized inverse distance weights.[45] I later explore alternative weight matrices, but results remain stable.

Table 6 presents regression results based on OLS and SEM for pooled and state fixed-effects models. The first observation is that disturbances are spatially correlated in the pooled OLS model (column 1) as indicated by Moran's I statistic (42.2) and a classic Lagrange Multiplier (LM) test for spatial error dependence (LM-Err= 1776.6).[46] It is natural then, for the SEM to capture this spatial error correlation ($\rho = 0.755$, column 2). If one ignores this positive spatial error dependence, it should lead to overconfident standard errors for OLS, but not to bias of regression coefficients.

Pace and LeSage (2008) developed a spatial Hausman test for this situation. If the DGP is truly SEM (null), both models are consistent but OLS is inefficient. If one rejects this hypothesis, it indicates the spatially-dependent error is correlated with the explanatory variables. Indeed, as illustrated in section II., omitted variables affect these two models differently, so their presence lead to divergence in their estimates. A spatial Hausman test comparing results from columns 1 and 2 of table 6 yields a test statistic of -446.4, which rejects the null.[47] However, this is a joint test for *all* coefficients and may be

[45]Unless otherwise noted, all weight matrices in the rest of the paper correspond to this weight matrix. I choose this one in particular because it yields the highest value of the likelihood function when spatial models are estimated via ML. Stakhovych and Bijmolt (2009) show in a Monte Carlo study that this procedure increases the probability of obtaining the correct weight matrix. This matrix was also considered in SHFb.

[46]Notice that the LM test for the presence of a spatial lag of the dependent variable (LM-Lag) is also significant. However, this could be reflecting the spatial correlation of disturbances.

[47]Under the null, the test statistic is distributed $\chi^2(14)$. The corresponding p-value is under 10^{-16}.

Table 6: Selected Regression Results for OLS and SEM

Dependent variable	(1)		(2)		(3)		(4)	
Farmland value (1987-2012)	OLS		SEM		OLS + FE		SEM + FE	
Intercept	8.281	**	7.153	**	6.736	**	5.872	**
Degree-days (8-32°C)	0.0001923		0.0002719		0.001199	**	0.0008196	**
Degree-days (8-32°C) squared	-9.06E-08	**	-6.08E-08		-3.26E-07	**	-1.79E-07	**
Degree-days (>34°C) squared root	-0.1645	**	-0.1407	**	-0.08849	**	-0.09241	**
Precipitation	0.006036	**	0.004844	**	0.003765	**	0.00441	**
Precipitation squared	-4.93E-06	**	-3.62E-06	**	-2.57E-06	**	-3.24E-06	**
Average water capacity	2.671	**	1.971	**	2.08	**	2.375	**
Clay content	-0.0002011		0.0003533		-0.0001277		0.0002266	
Minimum permeability	0.005638	**	0.001949		-0.0003363		0.001852	
K-factor of topsoil	-1.032	**	-0.7602	**	-0.7803	**	-0.7174	**
Best soil class	0.2869	**	0.1386	**	0.1939	**	0.1238	**
Latitude	-0.0874	**	-0.04603	**	-0.06118	**	-0.03212	*
Income per capita	3.15E-05	**	1.74E-05	**	2.55E-05	**	1.64E-05	**
Population density	0.003238	**	0.001689	**	0.002669	**	0.001581	**
Population density squared	-4.94E-06	**	-1.88E-06	**	-3.75E-06	**	-1.56E-06	**
Spatial correlation (ρ)	-		0.755	**	-		0.706	**
State fixed-effects (FE)	No		No		Yes		Yes	
Observations	2,274		2,274		2,274		2,274	
Moran's I standard deviate $N(0,1)$	42.2	**			39.9	**		
LM-Err $\chi^2(1)$	1776.6	**			1582.3	**		
LM-Lag $\chi^2(1)$	2139.4	**			1926.0	**		
RLM-Err $\chi^2(1)$	182.2	**			94.0	**		
RLM-Lag $\chi^2(1)$	427.6	**			437.7	**		

Notes: * and ** indicate statistical significance at %5 and 1% levels. For clarity of exposition, only regression results for the average land value for 1987-2012 are presented. All SEM models are estimated using a queen contiguity matrix and row-standardized inverse distance weights.

reflecting a correlation of the error with the control variables only, not with the climate variables of interest. I thus perform the test excluding all control variables and the test statistic is -2234.5, which leads to an even stronger rejection.[48] This indicates the presence of omitted variables in the OLS and SEM pooled models.

It is possible that this correlation is introduced by omitted factors occurring at the state level, such as differences in government payments or state policies. I thus present results for OLS and SEM model with state fixed-effects in columns 3 and 4 of 6. I perform the spatial Hausman test comparing these two models and obtain a test statistic of 248.6, which also rejects the null.[49] I perform the same test dropping all control variables and obtain a test statistic of 3595.6, which leads to a stronger rejection.[50] This result suggests that, even within states, there are omitted variables in the error term that are correlated with the included climate variables of interest. This is a new result that indicates that climate change impact projections based on either pooled or state fixed-effects OLS and SEM are unreliable.

To get a sense of the climate change impacts implied by the state fixed-effects models based OLS and SEM, I present their associated projections in figure 2. The first observation is that impact projections are more detrimental based on OLS than on SEM.[51] For the 1987-2012 average cross-section, the mid-century predicted farmland change under RCP8.5 is -61.5% and -50.2% for OLS and SEM, respectively. In section II. I discussed how bias in OLS is amplified to a greater extent than for SEM. It logically follows that the bias affecting these two models is downward, toward more negative and detrimental results.[52]

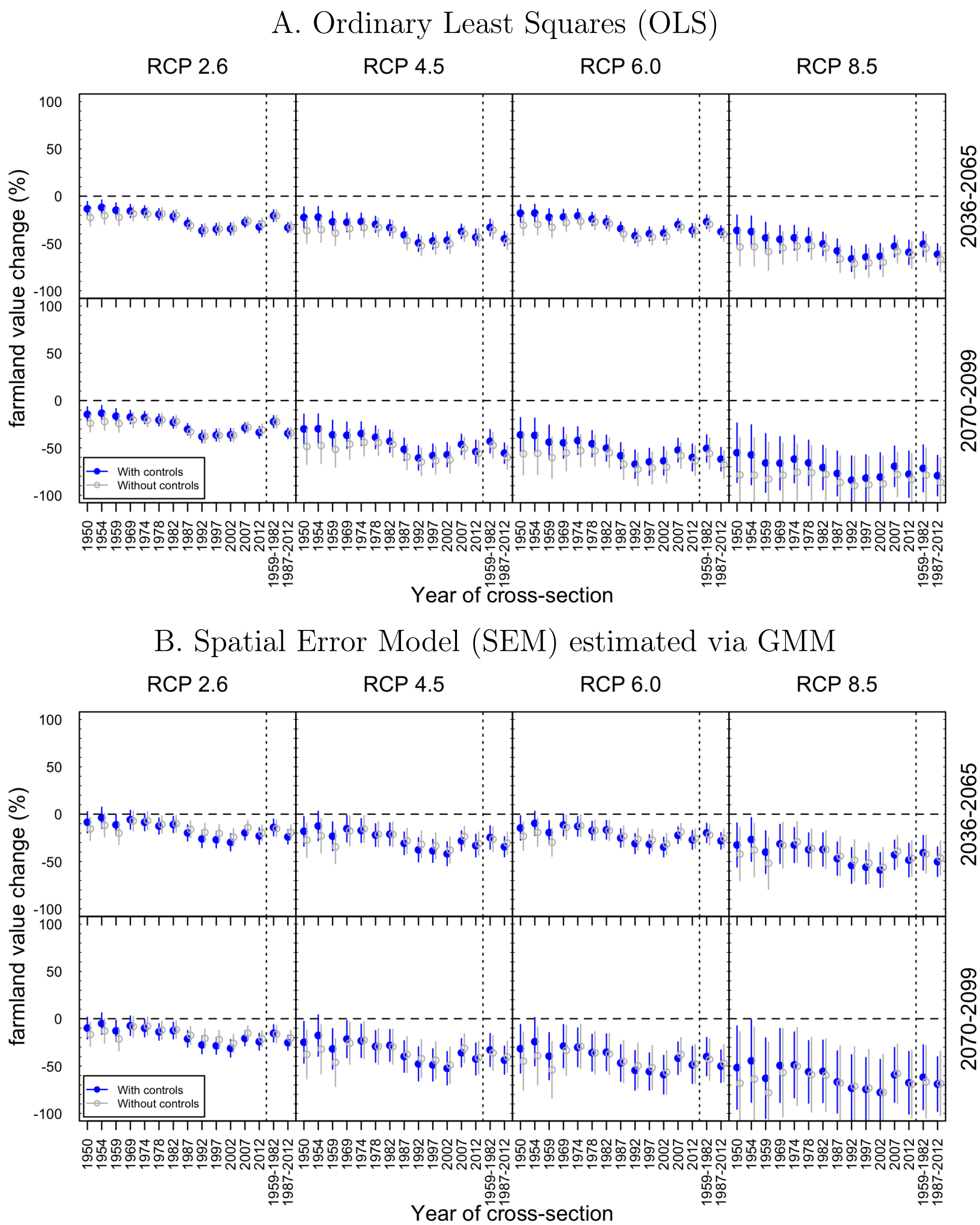
[48]The test statistic is distributed $\chi^2(6)$ under the null. The associated p-value is naturally also under 10^{-16}.

[49]Under the null, the test statistic is distributed $\chi^2(50)$. The corresponding p-value is under 10^{-16}.

[50]Under the null, the test statistic is distributed $\chi^2(41)$. The corresponding p-value is below 10^{-16}.

[51]Projections appear statistically different at a 1% level. However the result is to be handled with care given that the standard errors of OLS are biased downward.

[52]Results for pooled OLS and SEM are more negative and are provided in appendix A3.



Notes: Farmland value percent changes correspond to the farmland-weighted sample average projection. The top (bottom) row of each panel corresponds to the predicted farmland value change for 2036-2065 (2070-2099) relative to the 1976-2005 reference period. RCP scenarios increase in severity from left to right as described in section III.. The confidence bands represent 95 percent confidence intervals for the predicted mean change. Blue solid dots represent full models while hollow grey dots represent models without control variables.

Figure 2: Climate Change Impacts Based on OLS and SEM with State Fixed-Effects

A puzzling characteristic of figure 2 is that damage projections tend to attenuate for older cross-sections. In fact, for some scenarios and early time periods, the SEM points to barely significant impacts. Previous implementations of the hedonic model do not rely on older census data. As discussed in section I., the rationale for estimating the hedonic model for several cross-sections is to assess its stability and robustness under the presumption that the correlation of omitted variables with climate variables changes over time. Stable results across various cross-sections signal robustness. As previously discussed, the farmland value cross-section has changed substantially over the study period, mostly driven by factors that seem unrelated to agriculture. Moreover, projections based on models without control variables suggest this attenuation is not driven by changes in control variables either.

Recall that OLS and SEM estimates diverge in the presence of omitted variables. One could rely on the evolution of the spatial Hausman test statistic over cross-sections to assess the strength of the presence of omitted variables over time. I perform these tests and find that the test statistic increases in magnitude for more recent cross-sections.[53] This evidence indicates that while omitted variables affect all cross-sections, the presence of omitted variables seems stronger for recent cross-sections. It turns out these recent cross-sections point to larger damages, suggesting that large estimated damages are at least partly driven by omitted variables whose influence has increased over time. Although not conclusive, this pattern is consistent with the rise of the option value of farmland over time. If farmer's expectation about future land use conversions are well anchored, the option value should diminish as we consider earlier cross-sections. Therefore the option value of farmland is a plausible omitted variable in this context.[54]

[53] I perform these tests on the pooled model without control variables to avoid the influence of coefficients related to state dummies and control variables. The test statistic is distributed $\chi^2(6)$ under the null and the p-values are all below 10^{-6}. The spatial Hausman test statistics are 107.4 (for the 1950 cross-section), 39.4 (1954), -187.5 (1959), -125.0 (1969), -277.4 (1974), -399.3 (1978), -299.1 (1982), -576.3 (1987), -666.5 (1992), -908.7 (1997), -855.5 (2002), -726.4 (2007) and -568.4 (2012). The test statistics for averaged cross-sections are -525.3 (1959-1982) and -1018.4 (1987-2012).

[54] An interesting finding is that the coefficient for "Best soil class", which measures the share of high-quality soil in a county, steadily decreases for more recent cross-sections. This

In summary, impact projections based on either pooled or state fixed-effects OLS or SEM appear unreliable due to the presence of omitted variables. Damage projections for OLS are more detrimental suggesting, according to theory, that omitted variable bias in both OLS and SEM is toward more negative effects. This bias seems to strengthen for more recent cross-sections, as indicated by a growing spatial Hausman statistic. This is consistent with the rise of the option value of farmland which seems correlated with climate and strongly influences farmland values.

B. A General Spatial Hedonic Model

In this section I present regression results and climate change impact projections for the preferred model in this paper. I augment the specification of the baseline models with an endogenous spatial lag of the dependent variables and the explanatory variables. This is the SDM which I estimate via ML:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\phi + \mathbf{W}\mathbf{X}\theta + \epsilon \tag{5}$$

As discussed in section II., the exact nature of the functional form of the omitted variables is unknown. I therefore present both non-corrected and bias-corrected results. Non-corrected results are directly based on the reduced-form estimates of ϕ and θ. Recall these are biased estimators of β but do not have the bias amplification of OLS and SEM in the presence of a spatially correlated omitted variable.[55]

Before I proceed, it is worth noting that OLS results presaged the suitability of the proposed model. LM tests on OLS residuals can provide insights to discriminate between alternative spatial models. Recall that both LM-Err

suggests that the soil qualities that are inherently valuable for agriculture are having a decreasing role in determining the market value of farmland over time. The associated coefficients are: 0.4922 (for the 1950 cross-section), 0.4913 (1954), 0.4718 (1959), 0.5453 (1969), 0.4043 (1974), 0.3601 (1978), 0.3527 (1982), 0.1619 (1987), 0.2332 (1992), 0.1939 (1997), 0.1025 (2002), 0.08546 (2007), 0.1965 (2012). All coefficients are significant at a 10% level at a minimum.

[55]Because OLS and SEM estimates differ indicating both of those models are biased, then the non-corrected SDM must also be biased, but less so.

and LM-lag tests were statistically significant (columns 1 and 3 of table 6). However, these tests assume that the spatial dependence is either in the error or present as a spatial lag of the dependent variable, not both. Anselin et al. (1996) developed robust tests (RLM-Err and RLM-Lag) that account for the joint presence of both types of spatial dependence. Table 6 shows these robust tests are significant, providing evidence for both error dependence and the presence of a spatial lag of the dependent variable in the underlying DGP. In such circumstances, the use of the SDM is recommended (Elhorst, 2010).

However, we can test directly whether the SDM fits the data better than other models. Recall that the SDM presented in equation (3) simplifies to OLS or SEM when $\rho = 0, \theta = 0$ and $\phi = -\theta/\rho$, respectively. As previously mentioned, the latter is the common factor restriction and can be tested via a LR test when both models are estimated via ML. I test this restriction and the SEM is rejected for *all* cross-sections.[56] Therefore, evidence based on OLS residuals as well as direct testing of models points to the adoption of the SDM.[57] This result corroborates the finding of the spatial Hausman tests that indicate the presence of a spatially dependent omitted variable in OLS and SEM.

Table 7 presents regression results for the non-corrected SDM.[58] Because there is an endogenous lag of the dependent variable, SDM coefficients do not have the same marginal interpretation of a classical linear model. The compu-

[56]Under the null, the LR test statistic is distributed $\chi^2(14)$ and the test statistics are 184.4 (for the 1950 cross-section), 201.9 (1954), 214.0 (1959), 193.7 (1969), 232.7 (1974), 250.6 (1978), 184.0 (1982), 233.9 (1987), 208.9 (1992), 244.8 (1997), 236.7(2002), 184.8 (2007), 163.2 (2012), 161.8 (1959-1982) and 225.5 (1987-2012).

[57]I also perform additional LR tests to discriminate between the SDM and a model for which $\beta_{\mathbf{i}} = 0$, and those tests also lead to rejections of the restricted model. The restricted model in this case is the Spatial Autoregressive Model (SAR) with a DGP of the form $\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\phi + \epsilon$.

[58]Because the SDM exploits local variation in the independent and explanatory variables, a specification with state fixed-effects would not be sensible. Such a model *can* be estimated mechanically, but would introduce artifacts. More precisely, the weight matrix $\mathbf{W}$ performs local weighted averages of neighboring counties. In the state fixed-effects specification, the data is demeaned by the state mean. Differences in demeaned values between adjacent counties located in *different* states is not meaningful, but would be used in the calculation of the spatial lags $\mathbf{W}\mathbf{y}$ and $\mathbf{W}\mathbf{X}$. This procedure would therefore introduce and possibly amplify non-meaningful between-state variation in the estimation.

Table 7: Selected Regression Results for SDM

Variable	Direct Effect		Indirect Effect	
Degree-days (8-32°C)	-0.0006971	*	0.0008081	
Degree-days (8-32°C) squared	1.51E-07	*	-2.08E-07	
Degree-days (>34°C) squared root	-0.04432	*	-0.0792	*
Precipitation	0.003334	**	0.002062	
Precipitation squared	-2.57E-06	**	-1.63E-06	
Average water capacity	1.967	**	0.8095	
Clay content	0.0003951		-0.001317	
Minimum permeability	0.001068		-0.004149	
K-factor of topsoil	-0.6375	**	-0.8305	
Best soil class	0.06533	*	0.06573	
Latitude	-0.1785	**	0.1056	*
Income per capita	1.87E-05	**	4.80E-05	**
Population density	0.002004	**	0.007236	**
Population density squared	-2.72E-06	**	-1.49E-05	**
Spatial autoregressive parameter (ρ)	0.8461	**		
Log-likelihood	1,001.4			
AIC	-1,940.9			
Observations	2,274			

Notes: * and ** indicate statistical significance at 5 and 1 percent level. The dependent variable is the average of the log of farmland values for 1987-2012. I follow the approach in LeSage (2008) and LeSage and Pace (2010) and report the direct and indirect effects of explanatory variables on farmland values, rather than estimated coefficients. These are non-corrected results based on the reduced form estimates of ϕ and θ.

tation of marginal effects of explanatory variables on the dependent variable and their standard errors is somewhat involved. For clarity of exposition, I follow the approach in LeSage (2008) and LeSage and Pace (2010) and report the direct and indirect marginal effects of explanatory variables, rather than coefficients. These effects have the familiar marginal interpretation and are fairly insensitive to changes in $\mathbf{W}$.

Results in table 7 confirm there is a strong spatial dependence in the model as indicated by a significant autocorrelation parameter ($\rho = 0.841$). Climate variables exhibit significant direct effects but mostly for precipitation. The degree-days variables are now only significant at the 5% level.[59] The economic controls have direct effects that are highly significant. On the other hand, the indirect effects of climate variables are tenuous. Only the degree-days variable for extreme temperature is significant at the 5% level. However, the indirect effects of the economic controls are highly significant.

Climate change impact projections based on the SDM are presented in figure 3 for all cross-sections. Because OLS and SEM are found to be biased downward, SDM should also be biased downward, but less so. Therefore, it is not surprising that climate change impacts for the SDM remain slightly negative in panel A for recent cross-sections. However, all impacts are statistically insignificant at a 5% level, even for the most extreme RCP 8.5 scenario at the end of the century. Moreover, the SDM impact projections are statistically different from impacts projections based on the SEM. On the other hand, the bias-corrected SDM (with $\hat{\beta} = -\hat{\theta}/\hat{\rho}$) points to slightly more optimistic results in panel B. This was expected given the downward direction of the bias. However, the associated confidence bands are much wider due to the less precise estimation of the variance of the structural parameters.

To put these results in context, I present impact projections for the 1987-2012 averaged cross-section for all models in table 8. Results based on the state fixed-effects SEM specification are very similar to those found in SHFb.[60] For the SEM with state fixed-effects, the climate change impact toward the end of the century and under the extreme RCP8.5 scenario is -69.0% change in farmland values with a 95% confidence interval of -97.9 to -40.1%. This is equivalent to a 36.1 billion annual loss in profits.[61] On the other hand, the

[59] Note the direct effect for the degree-days for extreme temperature ($> 34°C$) has a substantially lower magnitude than for OLS or SEM models presented in table 6.

[60] SHFb finds impacts of -27.4, -31.6, -61.6 and -68.5% for the B1, B2, A2 and A1F1 climate change scenarios for the end of the century. In this paper I find impacts of -25.3, -43.8, -50.1 and -69.0% for RCP 2.6, 4.5, 6.0 and 8.5 climate change scenarios. Although these scenarios are not equivalent, they show high agreement between low and high warming scenarios.

[61] The total value of farmland for the sample is approximately $1 trillion USD (2012$). This is calculated by multiplying the average farmland value for 1987-2012 by the average number of farmland acres in the same period. Assuming a 5% capitalization rate this is equivalent to a yearly profit of $52.258 billion (G$).

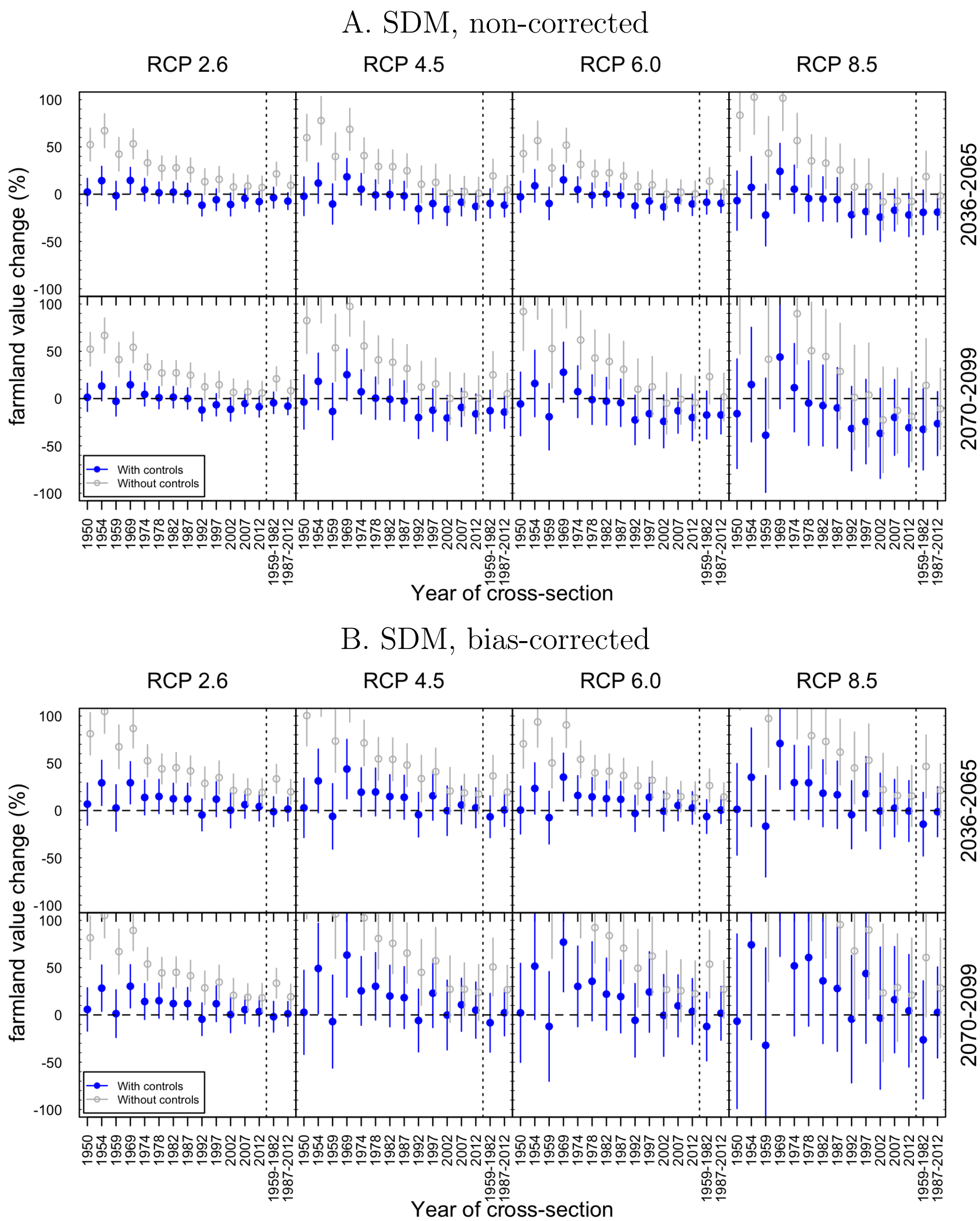


Figure 3: Climate Change Impacts Based on SDM

corresponding impact projection for the non-corrected SDM is -26.5% change in farmland values, or a 13.8 billion profit loss per year, with a 95% confidence interval of -60.3 to +7.3%.

The impact ratio column of the table shows the ratio of the OLS and SEM impacts relative to those of the non-corrected SDM. The column shows that damages based on OLS and SEM are 2.6 to 5.8 times greater than damages based on the non-corrected SDM specification, depending on the scenario or time horizon. These differences are statistically significant. Interestingly, the magnitude of this ratio closely matches the order of magnitude of the theoretical bias amplification found in section II.. Although the SDM impacts are not distinguishable from zero, the result is biased downward, although without amplification. The bias-corrected SDM points to a statistically insignificant +2.6% change in farmland values, or a 1.4 billion gain in yearly profits, but the associated confidence interval is much wider for this scenario.

The table shows that both the non-corrected and bias-corrected SDM point to impacts of climate change that cannot be distinguished from zero under all scenarios and time horizons. This result is statistically different from the impact projections based on the SEM, which serves as the reference cross-sectional model in the literature. Because the SDM subsumes the SEM as a special case, and that various tests conclusively suggest that the SDM fits the data better, these results rule of large benefits or damages from climate change on eastern US agriculture.

C. Robustness Checks

Here I explore the robustness of the results presented in this paper. I explore issues related to multicollinearity, the role of the endogenous spatial lag, the stability of results across spatial weight matrices, climate variables, dependent variables and regional subsets of the data.

A potential concern with the SDM is that the inclusion of the spatial lag of climate variables may lead to multicollinearity. Indeed, the spatial lag of climate variables are highly correlated with the climate variables. However, this problem would lead to wider confidence intervals for impact projections, not

Table 8: CLIMATE CHANGE IMPACTS FOR ALL MODELS UNDER ALTERNATIVE SCENARIOS

	2036-2065				2070-2099			
Model	Impact (%)	95% C.I. (±, %)	Impact (G$/yr)	Impact Ratio	Impact (%)	95% C.I. (±, %)	Impact (G$/yr)	Impact Ratio
				Hadley GEM2-ES, Scenario RCP 2.6				
OLS - pooled	-42.1	4.5	-22.0	5.8	-43.5	4.6	-22.8	5.4
OLS - state FE	-33.2	5.4	-17.4	4.5	-34.7	5.5	-18.1	4.3
SEM - pooled	-31.7	7.6	-16.6	4.3	-33.3	7.7	-17.4	4.2
SEM - state FE	-24.0	7.6	-12.5	3.3	-25.3	7.8	-13.2	3.2
SDM - non-corrected	-7.3	8.9	-3.8	1.0	-8.0	9.1	-4.2	1.0
SDM - bias-corrected	1.5	12.6	0.8	.	1.2	12.9	0.6	.
				Hadley GEM2-ES, Scenario RCP 4.5				
OLS - pooled	-55.0	6.0	-28.7	4.7	-65.8	8.4	-34.4	4.6
OLS - state FE	-45.0	7.6	-23.5	3.9	-55.6	10.7	-29.0	3.9
SEM - pooled	-44.5	10.2	-23.2	3.8	-54.6	14.4	-28.5	3.8
SEM - state FE	-34.4	10.6	-18.0	3.0	-43.8	14.8	-22.9	3.1
SDM - non-corrected	-11.6	12.3	-6.1	1.0	-14.2	17.2	-7.4	1.0
SDM - bias-corrected	0.7	17.5	0.4	.	2.3	24.4	1.2	.
				Hadley GEM2-ES, Scenario RCP 6.0				
OLS - pooled	-47.8	5.0	-25.0	5.0	-71.8	9.5	-37.5	4.2
OLS - state FE	-37.5	6.3	-19.6	3.9	-61.9	12.4	-32.4	3.6
SEM - pooled	-37.9	8.4	-19.8	3.9	-61.5	16.4	-32.1	3.6
SEM - state FE	-28.2	8.7	-14.7	2.9	-50.1	17.1	-26.2	2.9
SDM - non-corrected	-9.6	10.0	-5.0	1.0	-17.3	20.1	-9.0	1.0
SDM - bias-corrected	0.5	14.2	0.3	.	1.7	28.4	0.9	.
				Hadley GEM2-ES, Scenario RCP 8.5				
OLS - pooled	-70.8	8.4	-37.0	3.7	-87.2	15.7	-45.5	3.3
OLS - state FE	-61.5	11.2	-32.1	3.3	-79.3	21.3	-41.5	3.0
SEM - pooled	-61.3	14.6	-32.1	3.2	-79.4	27.3	-41.5	3.0
SEM - state FE	-50.2	15.5	-26.2	2.7	-69.0	28.9	-36.1	2.6
SDM - non-corrected	-18.9	18.7	-9.9	1.0	-26.5	33.8	-13.8	1.0
SDM - bias-corrected	-1.3	26.4	-0.7	.	2.6	48.0	1.4	.

Notes: Percent impacts are computed as $100(\exp(\Delta\mathbf{X}\beta) - 1)$, where $\Delta\mathbf{X}\beta$ are log farmland changes driven by changes in climatic variables only. $\Delta\mathbf{X}$ is computed as the farmland-weighted change in climate variables under each scenario. Confidence intervals for OLS are incorrect and biased downward because they ignore the positive spatial correlation of the errors. The impact ratio is the ratio between the mean impact for each model relative to the non-corrected SDM impact.

to bias. A comparison of figures 2 and 3 shows that statistically insignificant projections from the SDM do not stem from wider confidence intervals relative to SEM, but from point estimates that are closer to zero. Table 8 shows that the confidence intervals on impact projections are just about 20 percent larger for the SDM relative to the pooled SEM. Therefore results seem unaffected by this issue.

Another potential source of concern, is the endogenous spatial lag of the dependent variable $\mathbf{Wy}$ in the SDM. This term follows from re-arranging the model DGP with an omitted variable in a spatially correlated error term. Its purpose is to remove the spatial correlation of disturbances. A potential concern is that the spatial lag might be capturing too much of the spatial variation in farmland values. To verify this possibility, I estimate a model with the following form $\mathbf{y} = \mathbf{X}\phi + \mathbf{WX}\theta + \rho\mathbf{We} + \epsilon$, where the spatial dependence of unobservables is modeled in the error, rather than in the "mean" part of the model.[62] The results presented in appendix A5 show that the impact projections based on this model are virtually identical to those based on the SDM. This suggests that it is the spatial lag of regressors which are capturing the effect of omitted variables in the hedonic regression, as suggested by the theoretical model.

An important aspect of spatial models is the assumption on the $\mathbf{W}$ matrix. The one presented in the paper is based on queen contiguity and weights that decay with the reciprocal of the distance. This spatial weight matrix is also used in SHFb. That study finds results are largely unaffected by the choice of $\mathbf{W}$. Similarly, I find that impact projections are fairly insensitive to alternative weight matrices (in appendix A6).[63]

The main results presented in the paper are based on the degree-days variables and specification adopted in SHFb. To assess how results are affected by the choice of alternative climate variables I re-estimate the SEM (GMM)

[62]This model is commonly referred to as the Spatial Durbin Error Model (SDEM). It is a SEM augmented with a spatial lag of the independent variables. Unlike the SDM, the coefficients of the SDEM can be directly interpreted as marginal effects.

[63]The alternative weight matrices include queen contiguity with binary weights and nearest 7 and 15 neighbors with inverse distance weights. All weights are row-standardized.

with state fixed-effects and the SDM using linear degree-days variables and monthly climate normals following MNS.[64] I present results in appendix A7. The linear degree-days specification provides qualitatively similar results for both models to those provided in the paper so further discussion is not needed.

However, results based on monthly climate variables are different. For recent periods (1992-2012), the SEM points to negative impacts just as with the degree-days variables, but these projections become positive for older time periods (1950-1982). This result highlights that degree-days variables and monthly temperatures fit the data differently as suggested by SHFb. Because these are non-nested models we cannot rely on LR tests for model selection but on other criteria, such as AIC.[65] The AIC is slightly lower for models based on monthly climate variables compared to degree-days variables for all cross-sections, suggesting that, within-sample, monthly average climate variables seem to fit the data slightly better.[66] Irrespective of whether one set of climate variables is more appropriate than the other, this result indicates the SEM impact projections are unstable and change signs when monthly climate variables are used. In contrast, the SDM impact projections based on monthly climate variables are slightly more stable and do not point to negative impacts under any cross-section. Impact projections based on the preferred SDM suggest statistically insignificant impacts with these alternative climate variables.

Throughout the paper I suggest the option value of farmland as a likely omitted variable. Because farmland prices from the US Agricultural Census are based on farmer assessment of market value, these naturally reflect the option value of development opportunities outside of agriculture. In principle,

[64] The linear degree-days specification includes separate linear terms for degree-days 10-30°C and >30°C as well as linear and quadratic precipitation variables. The monthly climate variable specification includes linear and quadratic terms for monthly mean temperature and precipitation normals for the months of January, April, July and October.

[65] This requires, however, that the SEM is estimated via ML, not GMM.

[66] This is a little surprising given that SHFb find that degree-days variables provide a superior fit. However, their comparison is performed out of sample, and not based on AIC. However, it is evident that models based on degree-days are considerably more stable across cross-sections.

one could circumvent this issue by using a more direct measure of agricultural productivity, such as the rental price of farmland, which should not reflect its option value. However, only the rental price of *cropland*, a subset of farmland, is available for recent years.[67] This latter variable is somewhat problematic because the share of cropland in the rental market varies considerably across the country and there are many counties with missing observations. Thus, the associated results could be based on a skewed sample. Nevertheless, I present results based on this variable for pooled OLS, SEM (GMM) and SDM in appendix A8. Interestingly, results based on OLS and SEM point to negative but smaller damages than for models based on farmland values. However, these results are affected by omitted variables as indicated by a spatial Hausman test. On the other hand, the SDM results are less negative but remain statistically insignificant.

Finally, I present results based on alternative regional subsets. I divide the eastern US sample into North/South and Central/East subsamples and run the SDM for each group. The subsamples and the results are presented in appendix A9. Impact projections are noisier and become slightly negative only for the "East" subsample. However, this subsample contains most of the "high-ratio" counties of figure 1 and is where the effect of omitted variables appears to be the strongest. As a result, these findings support results based on the SDM.

V. Conclusion

There's been a lively debate regarding the potential impacts of climate change on US agriculture. Studies based on the hedonic approach such as Schlenker et al. (2005) and Schlenker et al. (2006) find large detrimental effects of climate change on US agriculture. I find similar results based on the SEM used in the latter study, with a projected impact of -69.0% change in farmland values, or an annual loss of $36.1 billion, under the most severe climate change scenario for the end of the century. However, this result is vulnerable to slowly-varying or

[67]The data is from the Cash Rent Survey as indicated in section III..

time-invariant omitted variables. More importantly, I argue that confounders, if present in this context, are likely to be spatially dependent given the nature of all suspect variables that have been proposed and the spatial dependence of all controls variables used in this literature. This feature, as I illustrated, can compound omitted variables bias severalfold.

In this paper I propose a hedonic approach for estimating the impacts of climate change on agriculture that is robust to spatially-dependent omitted variables. I exploit the fact that certain estimators amplify the bias from such confounders to varying degrees, to detect the sign and magnitude of the bias and correct for it. Theoretically, I predict that OLS and the SEM amplify such biases by a factor of 3.3 and 2.3-3.0, respectively, while the preferred SDM has a neutral amplification of 1. In the absence of spatially-dependent confounders, OLS, the SEM and the SDM, should lead to statistically similar estimates and thus similar climate change impact projections. However, the presence of spatially-dependent confounders lead to divergence of estimates across estimators and therefore to divergence of climate change impact projections.

My empirical findings conclusively suggest that climate change impacts based on OLS or the SEM are biased downward severalfold. I use a spatial Hausman test to find that OLS and SEM estimates are statistically different for all cross-sections from 1950 to 2012, which confirms the presence of spatially-dependent confounders. Moreover, I infer the direction of the bias in US hedonic models is downward because climate change impact projections based on OLS are systematically more detrimental than for SEM and the bias amplification is larger for OLS.

Because the SEM is nested within the SDM I could test the common factor restriction via a LR test. I reject the SEM for all cross-sections, confirming again the presence of spatial omitted variables and indicating the superior fit of the SDM. In the presence of a spatially-dependent omitted variable the SDM is also biased, but without amplification. It is therefore not surprising that the SDM impact projections appear slightly negative although results are not statistically significant for any of the scenarios or time horizons. I find that OLS and SEM point to damages that are 2.6 to 5.8 times greater than for the SDM. This impact ratio interestingly matches the order of magnitude of the theoretical bias amplification mentioned above, which shows agreement between my theoretical predictions and assumptions and empirical findings.

Finally, I derive a bias-corrected SDM and find that impact are unsurprisingly more optimistic, although impacts remain statistically insignificant. The bias-corrected SDM points to a statistically insignificant impact of +2.6% change in farmland values, or an annual gain of $1.4 billion, under the most severe climate change scenario toward the end of the century. This contradicts previous detrimental effects found in the literature.

In this paper I find no evidence of large beneficial or detrimental impacts of climate change on US agriculture. This contribution can help rationalize the relative magnitude of projected climate change impacts stemming from alternative approaches that allow varying degrees of farmer adaptations. Methods that only allow short-run and within-year adjustments should naturally point to more detrimental effects than methods, such as the hedonic approach, that allow for long-run adaptations. Therefore, the findings in this paper need not be in conflict with the large negative effects of weather shocks on crops yields (e.g. Schlenker and Roberts, 2009) because such approaches allow for a narrower range of farmer responses and adjustments.

It is important to emphasize that the proposed approach is not a panacea for controlling any type of omitted variables in a cross-sectional setting. The SDM only eliminates the bias amplification -not the bias itself- from spatially-dependent omitted variables. It is subsequently possible to derive bias-corrected estimates which are robust to such confounders. However, the proposed approach is particularly well suited for our context in which omitted variables are, in all likelihood, spatially correlated.

Finally, I must highlight that the hedonic approach has several caveats related to its observational nature and its reduced form. Observational approaches rely on historical variation in the data to infer future responses. However, there are changes that are not perceptible in the data that will occur under climate change. These include the rise of carbon dioxide in the atmosphere, the depletion of aquifers or large-scale ecological changes that affect pest populations and thus agricultural production. These remain important unknowns and add to the uncertainty of these results. On the other hand, the reduced-form nature of this approach does not allow unpacking the mechanisms through which farmers adapt. More research is needed to identify the potentially fruitful pathways to enhance farmer adaptations to a changing climate (Ortiz-Bobea and Just, 2013). Finally, more research effort should focus in areas, such as sub-saharan Africa, where data is scarce and the potential effects of climate change on agriculture are likely to be most disruptive.

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