Financial Accelerator at Work: Evidence from Corn Fields*

Nittai K. Bergman, Rajkamal Iyer, and Richard T. Thakor†

Abstract

This paper tests financial accelerator models. Using a novel dataset on agricultural production, we examine how exogenous productivity shocks arising from variation in temperature are propagated into the future. We find that past weather shocks have persistent effects on land values and productivity up to two years following the shock. Propagation and amplification of productivity shocks are both significantly larger during the farm debt crisis of the 1980s and amongst farms in lower income counties. Finally, we find higher investment in farm equipment and decreased borrowing following a positive weather shock.

JEL Classification: D24, E22, G31, Q14

Key words: financial accelerator, amplification, productivity, collateral values, weather shocks, agriculture

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† Bergman: MIT Sloan School of Management and NBER, e-mail: nbergman@mit.edu; Iyer: MIT Sloan School of Management, e-mail: riyer@mit.edu; Thakor: MIT Sloan School of Management, e-mail: rthakor@mit.edu.

1 Introduction

The role of financial frictions in amplifying and propagating economic shocks has received significant attention in explaining fluctuations over the business cycle. Financial frictions introduce a wedge between the cost of external finance and the opportunity cost of internal funds. This external finance premium implies that the strength of firms' balance sheets will affect the manner in which their investment activity reacts to economic shocks. Since current firm investment affects future balance sheet strength, a dynamic feedback loop is created that intertemporally propagates and amplifies economic shocks. Theoretical models of this so-called "financial accelerator" have played an important role in the Macro-Finance literature (see, e.g., Bernanke and Gertler, 1989; Shleifer and Vishny, 1992; and Kiyotaki and Moore, 1997).[1]

In spite of their importance, empirically testing financial accelerator models has proven to be difficult. There are at least three reasons why this is the case. First, a clean test of any financial accelerator model would involve exploiting exogenous shocks to firm productivity that affect the strength of firm balance sheet. Such shocks are hard to come by empirically and are difficult to measure. Second, measuring firm productivity, in and of itself, is quite challenging. Indeed, standard productivity measures, such as TFP, are often residuals of regressions relating (mismeasured) outputs and inputs. Finally, testing financial accelerator models is complicated by the fact that obtaining clean measures of collateral values, which often play an important role in financial accelerator models, is quite difficult.

This paper tests the central predictions of financial accelerator models and measures the economic magnitudes of the underlying effects. In deriving our tests, we follow two canonical financial accelerator models. Following Bernanke and Gertler (1989), we first analyze the

[1] See also Brunnermeier, Eisenbach, and Sannikov (2012) for a recent review of the literature.

propagation of productivity shocks over time, showing how current shocks to productivity affect future levels of productivity. Second, following Kiyotaki and Moore (1997), we examine how current negative shocks to productivity translate into decreases in current and future asset values.

For our analysis, we focus on the agricultural sector in Iowa. This sector provides a natural setting, rich in data, to examine how shocks to productivity are propagated, both during normal times as well as during crises. As a source of identification, we use exogenous shocks to productivity arising from variation in weather. Such weather variation is well known to affect agricultural productivity, and at the frequencies in which our study is conducted, this variation is plausibly exogenous. To measure productivity, and relate it to productivity shocks as well as proxies of financial constraints, we exploit the rich data available on farm crop yields. Finally, focusing on the agricultural sector allows us to measure collateral values, as land is a main source of collateral for farms and data on farmland prices are readily available.

To examine the effects of exogenous productivity shocks on future productivity levels as well as on asset values, we assemble a yearly, county-level dataset of weather and farm data from a variety of sources. Specifically, we collect weather, farmland prices, and farm crop yields spanning the time period from 1950 to 2010. We supplement this data with data on investment in farm machinery from 1995 to 2010, and data on farm debt levels from 1959 to 2010. We exploit the well-documented finding in the agronomics literature that corn yields are highly sensitive to temperatures, especially during the flowering month of July (when pollination and fertilization of corn occur). As described below, corn yields are non-linear and non-monotonic in July temperature, with high and low values being associated with lower yields.

As a first step in understanding accelerator effects, we examine the relation between past weather shocks on future farm yields and land values. Since weather will affect farm productivity, farm balance sheets will vary with weather shocks. In line with accelerator models, weather shocks are thus expected to have persistent effects on future productivity and land values. We find that the effect of weather shocks is indeed persistent: past weather-driven shocks to productivity affect current farm yields, as well as current land values. These results hold after controlling for the direct effect of *current* weather on contemporaneous farm yields and land values. As such, they are not driven by any predictive power of lagged weather on future weather. Since all specifications include both year and county fixed effects, our identification strategy is driven by comparing, within a given year, counties that in the *past* received differential productivity shocks (as compared to their sample mean). Consistent with accelerator models, we find that, holding constant current weather, farms that experienced negative weather-productivity shocks in the past exhibit lower current productivity as well as lower land values.

To further investigate the persistence of weather shocks, and in particular the potential channel through which such an effect arises, we examine whether the persistence of weather shocks differs across counties with high and low per capita income. Financial accelerator models would predict that persistence and amplification of economic shocks should be higher when financial frictions rise. Thus, we expect that the persistent effect of weather shocks should be larger in lower income counties, where farm balance sheets are arguably weaker. Consistent with this, we find that in counties with lower per capita income, farm yields and land values do indeed display a higher sensitivity to past weather shocks.

We next analyze the persistence of productivity weather shocks during the 1980s farm debt crisis—a well-known period of financial constraints in the agricultural sector.[2] During the farm debt crisis, farmland values dropped precipitously and the supply of credit available to

[2] The farm debt crisis of the early 1980s was triggered by two main factors: a sharp increase in interest rates by the Federal Reserve and the imposition of an embargo on U.S. agricultural imports by the Soviet Union (FDIC, 1997).

farmers contracted sharply, resulting in a significant decline in farm solvency (see Calomiris, Hubbard, and Stock, 1986, and Hubbard and Kashyap, 1992). Financial accelerator models would predict that during times of crisis—when there is widespread disruption in debt markets and balance sheets of farms are weaker—the effect of past productivity shocks on current productivity and collateral values will be amplified. Consistent with this, we find that the sensitivity of farm yields and land values to past weather shocks does indeed increase during the 1980s farm debt crisis. The effect is economically substantial, with the sensitivity of yields and land values to past shocks increasing significantly during the debt crisis.

To further gain insight into the channel through which weather shocks have a persistent effect on productivity, we examine the effect of past weather shocks on investment in farm machinery. The internal workings of accelerator models rely on a dynamic feedback loop between the strength of firm balance sheets—which have real effects due to the presence of financial frictions—and firm investment activity (see, e.g., Bernanke and Gertler, 1989). We thus expect that, following a positive past productivity shock, firms will be able to increase investment and enhance productivity. This is precisely what the data show. Farms increase their investment into machinery after beneficial weather shocks. The results are thus consistent with the feedback effects in accelerator models: with positive productivity shocks, firms increase their investments into machinery and land, which in turn increases productivity in subsequent periods.

Finally, we examine the impact of weather shocks on the level of farm debt. Proxying for farm debt using the total amount of agricultural lending by banks within a county, we find that after a positive weather-driven shock, firms reduce borrowing. Thus, after a positive shock, firms borrow less (or pay down debt) and use more internal funds to finance investments. Greater availability of internal funds after a positive productivity shock seems to enable farms to reduce reliance on external finance, which, due to financial frictions, is more expensive than internal funds. In line with our previous findings, the magnitudes of these effects are significantly larger during the debt crisis as compared to during normal times.

While the results above suggest that the effect of past weather shocks on current yields and land values stem from the presence of financial frictions, we analyze other alternative explanations, perhaps most importantly, a biological channel related to the effect of weather on soil. In particular, weather shocks could have effects on soil quality, which in turn affect future yields and land values. To address this concern, we first include a host of contemporaneous soil quality measures as control variables. We find that the estimated effects of past weather shocks remain even after controlling for measures of soil quality. In addition, our finding that the effect of past weather shocks increases substantially during the 1980s farm debt crisis also speaks against the soil-biology channel. Specifically, while the financial accelerator framework predicts that the effect of past weather shocks will be intensified during periods of financial stress, a simple biology channel is invariant to financial frictions and would therefore not predict this. Similarly, the heterogeneous effects of past weather shocks on low versus high income counties would also not be predicted by a simple biology channel, as there is little reason to believe that the biological effect of weather on soil would vary in such a manner.[3]

To better understand the direct impact of weather variation on productivity and farmland values, we also interviewed directors and senior executives of the Farm Credit System.[4] These interviewees stated that one season of hot weather does not affect soil quality, and further, that one would need three to four consecutive years of hot temperature to have any impact on soil

[3] Note again that all regressions are run with county fixed effects and so identification is not driven simply by the fact that low-income counties may be comprised of lower quality farmland that is more sensitive to weather shocks.
[4] As discussed below, the Farm Credit System is a $248 billion nationwide network of agricultural lending institutions in the United States. Many of the directors interviewed also own large farms and cultivate corn.

quality.[5] Interviewees also confirmed that positive yield shocks affected farms' financial constraints, thereby impacting investment, productivity, land values, and more generally, local farm affluence.

As final evidence in favor of the financial accelerator, we find that the effect of past weather shocks on both land values and corn yields is not present in the latter part of the sample period, starting in 1990. This is consistent with the dramatic increase in the 1990s of large farming corporations within the industry. These large firms tend to be less constrained than the smaller farms that were more prevalent prior to this period. Large farming firms also brought about a change in the importance of localized economic conditions in pricing agriculture land. Finally, beginning in the 1990s, markets in crop insurance developed to the benefit of both large and smaller sized farms. In the context of a financial accelerator model, all three changes—the reduction in general financial constraints, markets for land becoming less localized, and the increased importance of hedging—would predict a muted effect of weather shocks in the latter part of the sample period, as the data show.

This paper most directly relates to the literature on financial accelerators. Most empirical work in this area relies on calibrations using aggregate-level data, often employing vector autoregression analysis that analyzes impulse response functions (see, e.g., Bernanke and Gertler, 1995, and Bernanke, Gertler, and Gilchrist, 1999). In contrast to this line of work, our paper exploits micro-level data to identify the financial accelerator channel. Our paper is also related to the vast literature on financial frictions, and in particular to studies relating firm investment behavior to their cash flows.[6] This large literature is focused on testing for the very

[5] This response is also consistent with the findings of many studies that soil quality does not vary much over time and is generally quite static (see, e.g., Deschênes and Greenstone, 2007).

[6] See, for example, Hubbard and Kashyap (1992); Blanchard, Lopez-de-Silanes, and Shleifer (1994); Kaplan and Zingales (1997); Rauh (2006); Mian et al. (2013); Chaney et al. (2012); and Krishnan et al. (2014).

existence of financial constraints. While such constraints are an important *ingredient* within financial accelerator models, the empirical literature on financial constraints does not deal with the main predictions of accelerator models—namely, the persistence and amplification of shocks over time. In particular, as opposed to this literature, we focus on the intertemporal transmission of productivity shocks into future changes in asset values and productivity levels.

Our results also add to the literature on cash-in-the-market pricing during financial crises (Shleifer and Vishny, 1992; Allen and Gale, 1994; Stein, 1995).[7] We find that the effect of weather shocks on land values is significantly larger during the farm crisis (by a factor of three). Indeed, favorable weather shocks during the crisis should be viewed as positive cash infusions for affected firms. As such, cash constraints become less binding, implying an increase in asset values and firm productivity. The results, therefore, suggest that equity-like interventions—cash grants, tax subsidies, payroll tax deductions—may be effective at stemming productivity losses and boosting collateral values during a crisis.

Finally, our results add to the literature that examines the role of credit constraints in the agricultural sector, especially in developing economies (see, Karlan and Murdoch, 2009; Beaman et al., 2014). The results show that temporary shocks to productivity can have persistent effects in the presence of credit constraints. If such constraints are large—as is generally thought to be the case in many developing countries—crop production and the agricultural sector will be particularly vulnerable to weather shocks.

The remainder of this paper is organized as follows. Section 2 describes our empirical methodology and the construction of our dataset. In Section 3, we report our empirical findings and the interpretation of our results. Section 4 concludes.

[7] See also Rajan and Ramcharan (2014a,b) for empirical evidence on the role of credit availability in determining the magnitude of farmland value boom and bust cycles during the Great Depression.

2 Empirical Methodology and Data

2.1 Empirical Strategy

Empirical identification of the financial accelerator is difficult. First, it is necessary to isolate exogenous shocks to productivity, as amplification and persistence of exogenous shocks are at the heart of financial accelerator models. Second, it is usually difficult to obtain clean estimates of firm productivity. Indeed, standard productivity measures, such as TFP, are often residuals of regressions relating (mismeasured) outputs and inputs. Third, data on collateral values are hard to obtain, in particular because collateral take a wide variety of forms across different firms and industries.

The agriculture sector provides a natural laboratory to overcome these challenges, allowing us to isolate and examine the effects of financial accelerator models. First, as a source of identification, we use exogenous shocks to productivity arising from variation in weather. An extensive body of literature has shown that variation in weather has a strong effect on agricultural productivity (see Dell, Jones, and Olken, 2014, for a review). This variation is exogenous to farm-level activity, certainly within the frequency we study. Second, the productivity measure we use is yield per acre of planted crop, a measure that is well known to vary with variation in weather. Third, we use the price of farmland as a measure of collateral value, since farmland is the main source of collateral in the farming business.

We focus on the state of Iowa, which provides an ideal setting for examining the effects of weather on agricultural outcomes. Agricultural production is significant in Iowa and constitutes a large portion of economic activity for the state.[8] Iowa also ranks first out of all states in terms of the production of corn, which is the most plentiful U.S. crop and which is also

[8] According to the Iowa Farm Bureau, the agriculture sector brings $72 billion into Iowa's economy each year and creates one out of every six new jobs.

well understood in terms of its growth response to temperature fluctuations. Finally, and most importantly, agricultural data for Iowa are available at a more detailed level and for a much longer time period compared to other states, allowing for a more complete time series of our empirical tests.[9]

Our main specification examines the persistent effect of past temperature shocks on current corn growing productivity, farmland values, debt, and investment. Corn is generally planted in Iowa in the last two weeks of April, with most of the corn harvested in October. While there are several factors that affect corn yields, high temperatures above a particular threshold, especially during the flowering month of July, when pollination and fertilization of corn occurs, has been documented in several studies as an important factor affecting yields (Thompson, 1963; Schlenker and Roberts, 2006, 2009).[10] To measure temperature shocks, we therefore construct county-level measures of average temperature in July for each year. To account for the non-monotonic effect of temperature, we follow the literature and include the square of July temperature in our specifications (see also Mendelson et al., 1994; Schlenker et al., 2005; Hornbeck, 2012). Our main specification, which includes two lags of weather shocks, is:

$$\begin{aligned}\log\left(Y_{i,t}\right) = b_0 &+ b_1\left(July\ Temp\right)_{i,t} + b_2\left(July\ Temp\right)_{i,t}^2 + b_3\left(July\ Temp\right)_{i,t-1} \\ &+ b_4\left(July\ Temp\right)_{i,t-1}^2 + b_5\left(July\ Temp\right)_{i,t-2} + b_6\left(July\ Temp\right)_{i,t-2}^2 \\ &+ \eta_t + \lambda_i + \varepsilon_{i,t}\end{aligned} \tag{1}$$

where $Y_{i,t}$ represents either average land value or productivity for county i in year t, *July Temp* represents the average temperature in July for county i in year t, η_t are year fixed effects, and λ_t

[9] Farmland values are only available for Agricultural Census years (at five-year intervals) for most other states.
[10] Corn pollination and fertilization occur in the month of July, representing a crucial phase of crop development. Any plant stress during this time can result in decreased yields. Schlenker and Roberts (2009) report that yields are increasing up to 29 degrees Celsius but that above this threshold there is a sharp decline in yields.

are county fixed effects.[11]

One question that often arises in using climate data is whether shocks to weather are independent and identically distributed. Regardless, for the purposes of our empirical strategy, we do not rely on the assumption that weather shocks are independent of each other: in all our specifications, we control for contemporaneous weather in order to take into account any autocorrelation in weather patterns.[12] As stated above, all regression specifications also include year fixed effects as well as county fixed effects to take into account time-invariant omitted characteristics at the county level (like soil quality), or county-invariant shocks such as technological shocks or variation in the price of corn that could affect productivity levels. Our identification strategy is thus driven by comparing, within a given year, counties that in the *past* received differential productivity shocks (as compared to their sample mean). Finally, we also calculate standard errors adjusting for spatial correlation, since geographically-adjacent counties are likely to have weather that is more positively correlated than counties that are further away from each other.[13]

One potential concern with the interpretation of the patterns found in the data is that a soil biology channel may be driving the results. For example, while including county fixed effects may control for geographical differences in soil quality that are invariant to time, it is possible that temporary bad weather shocks may affect soil quality reducing future productivity and land values. We address this important concern in Section 3.5 below.

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[11] We also run the estimations using the number of days in the growing season that are hotter than 83 degrees Fahrenheit to capture harmful effects of cumulative heat exposure, finding similar results (not reported). See also Massetti et al. (2014) for a discussion on the use of daily temperature versus the degree-days measure for estimating the effect of temperature on farmland values.

[12] In addition, we conduct placebo tests examining the effect of *future*, i.e., year t+1, weather variation on current, year t yields, and find no significant effects (see Table A1 in the Appendix).

[13] We use a uniform spatial weighting kernel, as in Conley (2008) with a distance cutoff of 100km. The results are robust to using other cutoffs such as 150km, 200km. See also Hsiang (2010).

2.2 Data Sources

We construct a novel dataset of agricultural crop productivity, land values, debt, and investment at the county-level for Iowa. Our dataset is constructed using a variety of different sources. For our weather data, we collect daily weather station data for the U.S. from the National Oceanic and Atmospheric Administration (NOAA) from 1950 to 2010. Using this daily data, we then calculate the average temperature for the month of July for each weather station.[14]

We then construct county-level estimates of average July temperature for Iowa using the procedure of Deschênes and Greenstone (2012). Using geographical data for each county in Iowa from the U.S. Census Bureau, we construct county-level average July temperature by using a weighted average of all weather station estimates within a 50km radius of the geographical center of each county. The weights are the inverse of the squared distance from each weather station to the geographical center of the county. As there are 99 counties in Iowa, this yields a total of 6,032 county-year temperature observations for our main regression specification. Our results are robust to an alternative construction of the weather dataset using the procedure of Schlenker and Roberts (2009).[15]

Our measure of corn yields come from the USDA's National Agricultural Statistics Service (NASS) yearly crop surveys. The NASS provides yearly data at the county level of average corn yields from 1950 to 2010, measured in bushels per acre harvested. Our measure of farmland values come from the Iowa State University Farmland Value Survey, which provides yearly county-level estimates (as measured in November of each calendar year) of the average value per acre of Iowa farmland from 1950 to 2010.[16] The respondents to the survey are

[14] In any given year, we only use weather stations that have non-missing data for every day in July.

[15] We thank Wolfram Schlenker for providing this data.

[16] A potential concern with the estimates of farmland value is that some parcels of land may be irrigated (thus leading to a higher value) while others may not. However, very little of the farmland in Iowa is irrigated, implying

individuals that are considered to be knowledgeable of land market conditions, such as agricultural real estate brokers. In each year, respondents are asked to provide their estimate of current farmland prices in the county they are located. Studies have shown that these survey values closely track actual land sales prices (see Stinn and Duffy, 2012, and Kuethe and Ifft, 2013). To proxy for farm balance sheet strength, we use county-level income per capita data from the Bureau of Economic Analysis. We take our data on soil quality from Deschênes and Greenstone (2007) who obtain National Resource Inventory (NRI) estimates of soil quality from various sites across the U.S. and construct county-level measures through these estimates. As NRI sites are not located in every county in Iowa, the data cover 33 counties and run every five years from 1978 to 2002.

Our measures of farm financial debt come from the Federal Reserve's Commercial Bank Data Call Reports. We use two measures of agricultural lending by banks. The first measure is total agricultural debt, which is defined as the combination of loans to finance agricultural production and real estate loans secured by farmland. The second measure is real estate loans secured by farmland. We construct county-level estimates of farm debt by summing all agricultural debt issued by banks located in the given county. The Call Report data run yearly from 1959 to 2010 (we use fourth quarter reports to construct end-of-year values). One shortcoming of the Call Report data is that all loans of a given bank are associated with the location of the headquarters of that bank. Results regarding debt levels should thus be interpreted with caution.

Finally, data on machinery investment are provided by EDA (Equipment Data

that this is not a concern for our sample. For example, according to data from the U.S. Agricultural Census and the NASS, only roughly 2.6% of total Iowa farmland was irrigated in 2012.

Associates), a data service provider that assembles proprietary data on farm machinery transactions that were financed through collateralized debt for the time period from 1995 to 2010. We construct yearly county-level estimates of machinery investment by summing the market value of farm machinery purchases in a given county and year. In doing so, we focus on farm machinery of the size class that is the most common in terms of number of transactions in order to capture more typical machinery investments. Examples of farm machines that fall into this class include corn heads, planters, cultivators, plows, tractors, and combines.

2.3 Summary Statistics

Summary statistics of all variables are provided in Table 1. As the table shows, the average temperature in July for Iowa counties is 74 degrees Fahrenheit (23.3 degrees Celsius). The overall standard deviation of temperature is roughly 2.87 degrees Fahrenheit, indicating a fair amount of variability in temperature.[17] Figure 1, Panel A reports the density plots of the distribution of temperature over our entire sample, as well as for a number of particular years in our sample. As the first plot indicates, the distribution of temperature across county-years in our sample appears bell shaped around a mean of 74 degrees, with a range from 65 degrees to roughly 85 degrees. The density plots for the individual years indicate substantial variability across counties for any given year, with some years exhibiting substantially higher mean temperatures. As our main specifications include county and year fixed effects, Figure 1, Panel A exhibits variation which we do not exploit in our identification strategy. Figure 1, Panel B therefore presents density plots of temperature variation demeaned with year and county fixed effects. The distribution of demeaned temperature for both plots are symmetric around zero, but

[17] As will be seen below, relatively small variation in average July temperature has a significant effect on corn yields.

also exhibit substantial variation. The within standard deviation of temperature is 2.552, and the between standard deviation is 1.318.

The productivity and economic outcome variables are given next in Table 1. The mean corn yield for counties in Iowa in our sample is roughly 107 bushels per acre of land harvested. Mean corn yields have increased over time from a value of 48.1 bushels per acre in 1950 to a value of 154.6 bushels per acre in 2010. The mean (real) value per acre of farmland for the sample is $2,777 per acre, again increasing over time from $1,916 per acre in 1950 to $5,062 per acre in 2010. The mean amount of total county-level agricultural debt is roughly $81.2 million (in real 2010 values), but this varies substantially across counties, with some having substantially more agricultural debt than others. County-level measures of soil quality (permeability, K-factor, and moisture capacity) are presented last in Table 1. The estimates do not vary much over time—the within standard deviation is close to zero—reflecting the fact that soil quality tends to be stable over time for a given geographical region.

Figure A1 depicts average corn yield, land value, and agricultural debt across all counties for each year in the sample. Average corn yield increases over the sample period, as would be expected with technological improvements in agriculture. Land values increase gradually from 1950 to 1970 and then substantially from 1970 to 1980. However, in the early 1980s, corresponding to the period of the farm debt crisis, land values drop precipitously. By contrast, corn yields do not exhibit such a trend during the debt crisis, suggesting that changes in land productivity were not responsible for the large decline in farmland prices. Finally, agricultural debt increases steadily from 1960 to 1980 but drops significantly during the farm debt crisis, as would be expected.

3 Empirical Results

3.1 Effect of Temperature Shocks on Corn Yields and Land Values

We begin the analysis by examining the effect of temporary temperature shocks on corn yields—i.e., agricultural productivity. In order to do so, we estimate regression (1) for our entire sample period relating temperature shocks and its lags to both yields and land values. The estimation results are given in Table 2. Column (1) includes the contemporaneous value of *July Temp* as well as squared *July Temp*. We find that *July Temp* has a positive and significant sign, while squared *July Temp* has a negative and significant sign. This indicates that increases in contemporaneous temperature have a positive effect on corn yields, but only up to a certain point. Extreme temperatures—either high or low—are detrimental to corn yields.

Column (2) adds lagged July temperature and temperature-squared to analyze the persistent effect of shocks on productivity. Again, the coefficient of $(July\ Temp)_{t-1}$ is positive and significant, while the coefficient of squared $(July\ Temp)_{t-1}$ is negative and significant: past temperature shocks thus have an effect on current corn productivity, with values either too high or too low reducing current yields. As would be expected, the magnitudes of the lagged coefficients are smaller than those of the contemporaneous coefficients, so that while the effects of temperature shocks are persistent, they diminish over time.

Columns (3) and (4) add temperature shocks from two-year and three-year lags to the regression covariates. The estimates are smaller than those for the first lag, and the coefficients are insignificant. Column (5) shows the results of regression (1) using robust standard errors clustered at the county level rather than spatially-corrected standard errors. When not correcting for spatial correlation, the effect of the persistence is stronger, as $(July\ Temp)_{t-2}$ and squared

(*July Temp*)$_{t-2}$ become significant.[18]

Figure 2, Panel A (left) exhibits the effect of past temperature on corn yields based on the regression estimates in Column (3) of Table 2. Yields achieve a maximum value at year t–1 *July Temp* of approximately 77 degrees Fahrenheit. Starting from this point and increasing one-year lagged temperature by three degrees—approximately the standard deviation of temperature—reduces current yields by 1.7 percent. By way of comparison, increasing temperature from 77 to 80 degrees Fahrenheit contemporaneously—i.e., in year t—reduces year t yields by 21 percent. Thus, the effect of lagged temperature shocks on future yields is 8 percent of the contemporaneous effect.[19]

Table 3 examines the effect of lagged weather shocks on land values by re-estimating regression (1) using land values as a dependent variable. As can be seen from Column (1), the effect of temperature on land values is similar to the effect of temperature on corn yields. The coefficient on (*July Temp*)$_t$ is positive and significant, and squared (*July Temp*)$_t$ is negative though insignificant. Column (2) includes one-year lags of temperature and its square, while Column (3) includes temperature and squared temperature up to two lags. For both the first and second lags, *July Temp* is positive and significant, while squared *July Temp* is negative and significant. Thus, good temperature shocks, both one and two years in the past, increase current land values, while bad temperature shocks in the past—i.e., high or low values of July temperature—decrease current land values. The effects die out by three years after the shock, as shown in Column (4). Column (5) reports the same results as Column (3) but with standard

[18] In unreported results, we control for July rainfall and its square, and find that July temperature continues to remain an important and significant predictor of yields. For robustness, we also estimate the model specified in Thompson (1963) that includes average contemporaneous temperature, precipitation for each month from May to August, pre-season precipitation, the squared terms of precipitation and temperature, along with interactions for temperature and precipitation for the months of June, July, and August. We find that July temperature is the most important determinant of corn yields.

[19] This 8 percent effect is very much in line with the estimation of economic magnitudes using the IV approach described below.

errors clustered at the county-level and not accounting for spatial correlation.

Figure 2, Panel A (right) illustrates the effect of one-year lagged temperature on current land values, using the regression estimates from Column (3). Consistent with the effects reported for corn yields above, increases in lagged temperature up to 77 degrees are beneficial to land values, while temperature increases beyond 77 degrees decrease land values. In terms of economic magnitudes, a three-degree increase in lagged *July Temp* from 77 degrees Fahrenheit to 80 degrees Fahrenheit—approximately a one-standard deviation change—reduces year *t* land values by 0.4 percent.[20]

The persistent effects of temporary temperature shocks on land values match the predictions of financial accelerator models. Indeed, there are two reasons for why positive weather shocks will increase land values in the presence of financial frictions. First, assuming some degree of localization in the market for land, positive weather shocks will increase the net worth of local buyers—i.e., nearby farmers—and hence push up the price of land. This is a cash-in-the-market pricing effect as in Shleifer and Vishny (1992) and Allen and Gale (1994).[21] Second, following positive weather shocks, buyers anticipate that they will be less financially constrained going forward, which in turn will enable them to increase future yields through productive investment. The increase in expected future yields will then be capitalized into land prices. This feedback loop between increased future productivity and asset values is discussed in Kiyotaki and Moore (1997).

To conclude, it is instructive to obtain a back-of-the-envelope estimate for the effect of weather shocks on farm balance sheets. First note that farming involves low profit margins—on

[20] Note that this estimate is derived from the entire sample period and not solely from periods of tight financial constraints, where balance sheet effects are predicted to be particularly large. Consistent with this, we find larger propagation effects of weather shocks on land values and yields during the 1980s farm debt crisis (described below).
[21] Note that some form of market segmentation is at the heart of accelerator models that rely on variation in asset values. For market segmentation in farmland, see, e.g., Rajan and Ramcharan (2014b).

the order of 6%.[22] Consider then a shock that shifts average July temperature from 77 to 80 degrees Fahrenheit, which as discussed above, reduces contemporaneous yields by 21%. Assuming conservatively that costs do not move following a bad weather shock, profits are expected to decline by 350%, implying a *loss* greater than three times the normal gain.[23] Thus, because of small profit margins, variation in weather can have a large influence on farm cash positions—a standard operating leverage effect—which can feed into land prices as well as farm investment.

3.2 Interaction of Financial Constraints with Temperature Shocks

We proceed by testing an important prediction of accelerator models—namely that amplification and persistence of temporary shocks should be more prevalent amongst financially constrained firms. As a first step, we proxy for local financial constraints using average county income per capita. We thus estimate regression (1) using corn yield as the dependent variable but include interactions of weather shocks with average county income per capita. The results are provided in Columns (1) through (3) of Table 4.

Column (1) of Table 4 shows the effect of the interaction of income per capita and lagged temperature on current corn yields. Similar to prior results, lagged *July Temp* enters with a positive sign and squared *July Temp* enters with a negative sign both contemporaneously and for the first lag. Lagged temperature shocks thus affect current year yields as shown above. Importantly though, the interaction between the lagged temperature terms and county income per capita enter with the *opposite* sign to the non-interacted temperature term (for example, the

[22] See USDA Economic information bulletin, May 2006.

[23] With a 6% profit margin, P=0.06R and C=0.94R, where P, R, and C are profit, revenue, and cost, respectively. Since the weather shock reduces revenue by 21%, the resultant profit, post-weather shock, will be -0.15R rather than 0.06R. Profit thus declines by 350%.

coefficient on *July Temp* × *Income Capita* in year t–1 is negative while that on *July Temp* is positive). Thus, consistent with the importance of financial frictions in amplifying shocks, the effect of variation in lagged temperature is larger in lower income counties.

Figure 2, Panel B (left) depicts these results graphically. The figure compares how corn yields respond to changes in lagged July temperature for a county in the 30th percentile of income per capita versus a county in the 70th percentile of income per capita. As can be seen, the curve for counties with higher income per capita is significantly flatter than that for counties with low income per capita, indicating that the response of yield to lagged temperature changes is smaller for wealthier counties.

While the effects are significant for temperature changes one year prior, they are insignificant for temperature changes two years prior (Columns (2) and (3) of Table 4), which is consistent with the results of Section 3.1 that the effects of temperature shocks on corn yields last for one year after the shock but are insignificant by two years after the shock.

We next examine the effect of the interaction of income per capita and temperature shocks on land values. The results are given in Columns (4) through (6) of Table 4. Once again, the interaction between the lagged temperature terms and county income per capita enters with the opposite sign to the non-interacted temperature term. Put differently, similar to the results on yields, land values in poorer counties are more sensitive to past temperature shocks than those in richer counties. Figure 2, Panel B (right) shows this effect graphically, comparing the response of land values to changes in prior year July temperature for a county in the 30th percentile of income per capita to a county in the 70th percentile of income per capita. As can be seen, the curve is flatter for higher income counties, indicating that land values are less sensitive to changes in lagged temperature in these counties. Similar to the results documented in Section

3.1, the effects last for two years after the initial temperature shock.

Interestingly, Table 4 also shows that the *contemporaneous* effect of temperature on yields is stronger in lower income counties. One explanation for this is that high income farms can utilize their financial resources to counteract the effect of bad weather by undertaking various costly adjustments. These might include more and higher quality fertilizer, greater labor investment, and more intensive capital use. In contrast, lower income farms cannot as easily counteract detrimental weather shock using costly alternate inputs. In a frictionless capital market, they would raise capital to do so, but in the presence of financial frictions, such financing is costly.[24] A similar pattern is observed with respect to land values: temperature has a greater effect on contemporaneous land values in low income counties as compared to high income counties.[25]

3.3 The 1980s Farm Debt Crisis

This section analyzes the propagation of productivity shocks during the 1980s farm debt crisis. This crisis provides an ideal setting to understand the quantitative effects of financial constraints on the accelerator mechanism during times when financial frictions are expected to be particularly large. Specifically, we explore how the impact of weather-driven productivity shocks on land values and future productivity are different over the full sample period (from 1950 to 2010) as compared to those exhibited during the farm debt crisis.

The farm debt crisis in the 1980s was triggered by the combination of a sharp increase in interest rates to combat inflation undertaken by the Federal Reserve under Paul Volcker and

[24] See Hornbeck (2012) for evidence suggesting that credit constraints inhibited farmers from making necessary adjustments to counteract the effects of large soil erosion during the 1930s American Dust Bowl.

[25] Recall that land values are measured in December of each calendar year—i.e., five months after the realization of July temperature.

Russia's imposition of an embargo on U.S. agricultural imports. The result was a period of severe financial distress for farmers leading to significantly weaker farm balance sheets (see Calomiris, Hubbard, and Stock, 1986). Financial accelerator models predict that during such a period, there will be an increase in the magnitude and persistence of past weather shocks on current productivity and asset (i.e., collateral) values. To analyze this prediction, we estimate regression (1) for corn yields and land values during the period of the farm debt crisis (from 1981 to 1986). The analysis is given in Table 5, with Columns (1) through (3) providing results for corn yields and Columns (4) through (6) exhibiting the results for farmland values.

As Table 5 shows, the signs of the coefficients on temperature are similar to those found above, and the persistent effects on both corn yields and land values are also present. However, the magnitudes of the coefficients are significantly larger than the magnitudes found in Table 2 and Table 3, which cover the entire sample period. As would be predicted by financial accelerator models, the effect of past temperature shocks on corn yields and land values are indeed larger during the farm debt crisis. Comparing the coefficients in Table 2 to those in Table 5 shows that the effect of lagged temperature on farm yields is 1.5 times larger during the debt crisis than over the entire sample period. Similarly, comparing Table 3 to Table 5 shows that the effect of lagged temperature on land values is three times larger during the debt crisis. Further, not only are the magnitudes of the lagged temperature coefficients larger, we also find that current yields are sensitive to weather shocks for up to two year lags, as compared to one year lag for the entire sample period. The persistence of shocks is therefore longer as well.

In terms of economic magnitudes, during the farm debt crisis, a three-degree increase in lagged *July Temp* from 77 to 80 degrees Fahrenheit—approximately a one-standard deviation change—reduces year *t* yields by 2.5 percent and land values by 1.3 percent. Note that, as in all specifications, the regressions in Table 5 are run with year fixed effects. The results are thus driven by variation in weather occurring within a year across different counties, and not by a general trend affecting all counties during the debt crisis, such as overall changes in investment opportunities.

Table 5 also shows that the effect of temperature on *contemporaneous* yields is far larger during the farm debt crisis as compared to the effect calculated over the entire sample period. For example, comparing Column (2) of Table 2 and Table 5 shows that the coefficients on $(July\ Temp)_t$ and squared $(July\ Temp)_t$ are approximately three times larger during the farm debt crisis than over the entire sample period. This result is similar to that found when comparing low income counties to high income counties described above: When financial constraints are tighter—as was the case during the 80s debt crisis—farms cannot easily substitute other inputs for bad weather shocks. Doing so will often involve raising external capital to finance additional inputs, which will be prohibitively costly, or simply unavailable, in periods of financial stress. As such, during crises farms are more vulnerable to detrimental variation in weather.

3.4 The Intertemporal Elasticity of Productivity

To further understand the economic magnitude of the propagation of productivity shocks over time, we employ an instrumental variable approach. Specifically, we run:

$$\log\left(yield_{i,t}\right) = b_0 + b_1(July\ Temp)_{i,t} + b_2(July\ Temp)^2_{i,t} + b_3\,\widehat{\log(yield)}_{i,t-1} + \eta_t + \lambda_i + \varepsilon_{i,t}\,, \quad (2)$$

where $\widehat{\log(yield)}_{i,t-1}$ is log yield instrumented with $(July\ Temp)_{t-1}$ and $(July\ Temp)_{t-2}$.[26] To understand the specification, note first that current—i.e., year t—temperature obviously has a

[26] As usual, η_t and λ_i are year and county fixed effects.

direct impact on year t yields, and is hence included as a control in the regression. The identifying assumption, however, is that *lagged* temperature, i.e. in years t–1 and t–2, affect current year t yields only through their impact on year t–1 yields and the resultant accelerator effects.[27] Under this identification assumption, lagged temperature exogenously shift lagged yields, and hence the coefficient b_3 provides an estimate of the elasticity of current yields to variation in past yields.

The results are shown in Table 6. Column (1) of the table shows the results of the first stage of the IV approach in which lagged yields, $\log(yield_{i,t-1})$, is regressed on all of the second stage control variables—$(July\ Temp)_t$, $(July\ Temp)_{t-1}$, $(July\ Temp)_{t-2}$, as well as their squares. Column (2) of Table 6 provides the results of the second stage, where $\log(yield_{i,t-1})$ is replaced by the predicted value from the first stage (as specified in estimation equation (2)). As can be seen from the coefficient on b_3, the intertemporal elasticity of yields is 0.094. Put differently, a 10% increase in productivity in year t implies a 1% increase in following year productivity. Column (3) of the table repeats the analysis but examines the intertemporal effect of productivity shocks on future asset prices by replacing log(*yield*) on the left hand side with log(*Land Value*). We find that the elasticity of year t land values to year t–1 shocks in productivity is 0.048.

3.5 The Biology and Optimism Channels

While the results above suggest that the effect of past weather shocks on current yields and land values stem from the presence of financial frictions, one important concern is that they are driven by a biological channel related to the effect of weather on soil. In particular, weather shocks could have long-lasting effects on soil quality, which in turn affect future yields and land values. The effect of weather shocks on land values and productivity would therefore be

[27] For example, this assumption would clearly be violated under the soil biology channel discussed in Section 3.6.

persistent not because of financial friction accelerator effects, but rather due to a direct biological channel.

We address this concern in a number of ways. First, we test whether the soil biology channel can account for our findings by including measures of soil quality over time as covariates in our baseline specification. We consider the three standard measures of soil quality: permeability; K-factor, which captures soil erodability; and soil moisture capacity. As discussed earlier, soil quality measures are from the National Resource Inventory (NRI) estimates of soil quality. Note that the NRI samples soil only every five years, and sites are not located in every county in Iowa so that data coverage is limited. The results are presented in Table 7.

Column (1) shows the results of temperature shocks on corn yields, after controlling for soil permeability and year fixed effects. High soil moisture permeability is good for soil growth, a fact reflected in the positive coefficient on the *Permeability* variable. Column (2) adds county fixed effects, which make the coefficient on permeability insignificant. This is consistent with the argument in the agricultural economics literature that soil variables are quite static and do not change dramatically over short periods of time. In both specifications, both with and without county fixed effects, the coefficients for the effects of temperature on yields remain significant. Columns (3) through (6) include K-factor and soil moisture capacity as control variables, both with and without fixed effects, showing similar results.[28]

In addition to directly controlling for soil quality, the results regarding the farm debt crisis and the heterogeneous effect of past weather shocks based on per capita income also speak against the biology channel. In particular, a simple biology channel in which weather directly affects soil quality would not predict an increase in the impact of weather shocks during the farm debt crisis, as we find in the data. Similarly, a direct biology channel in which soil quality is

[28] K-factor proxies for soil erodibility that is bad for plant growth.

changing with weather shocks would not naturally predict a stronger effect of weather shocks amongst poorer counties.

Another possible explanation for the impact of current weather shocks on future productivity and land values is a behavioral channel in which farmers overreact to small weather variations. For example, after observing a positive weather shock, farmers may believe that future weather patterns will be more favorable, and as a result, they increase investment as well as bid up the price of land. Current weather shocks would then be correlated with greater future productivity and farmland values. Refuting such a behavioral channel is difficult: as is always the case, individual behavioral biases can always be manipulated to fit the data. Still, the behavioral channel is hard to justify. First, it is not at all clear why farmers' behavioral response to current weather shocks, and their extrapolation of these shocks into the future, would intensify during farm debt crises. Similarly, given the data, one would need to argue that farmers in poorer counties suffer from greater behavioral biases than do those in richer counties—an observation that is arguably difficult to justify. Finally, we show below that the effect of weather on productivity and land values is concentrated in the pre-1990 sample period, a fact that a simple optimism channel would not directly predict.[29]

3.6 Effect of Temperature Shocks on Investment and Debt Levels

An important feature of many financial accelerator models is the link between productivity shocks and both current, as well as future, investment. According to this, temporary shocks to net worth have a persistent effect on firm investment and output: reduced financial

[29] An additional potential concern is that, when planting, farmers use seeds that are derived from their prior-year's crop. If seed quality deteriorates following a negative weather shock, this could explain the persistent effect of such shocks. However, corn seeds are generally purchased from seed companies, negating this concern. It is, of course, possible that financial constraints lead farmers to purchase cheaper, lower quality seeds, but this would be a particular manifestation of a financial accelerator effect.

constraints increases firm investment, which relaxes financial constraints in the future, in turn increasing subsequent investment still further. To analyze this feature within the context of our empirical framework, we estimate regression (1) using the value of machinery purchases as a dependent variable and include either one or two lags of temperature shocks.

The results are given in Table 8, Columns (1) through (3). As can be seen, the relation between temperature and investment is non-monotonic, with high or low temperature values—i.e., those associated with negative shocks—associated with reductions in investment. This effect is persistent as well—it lasts for a year following the initial shock, but then becomes insignificant two years following the initial shock.

We next analyze how temperature shocks affect farm debt levels. Within the context of accelerator models, while the effect of a past positive productivity shock on current productivity and land values is unambiguously positive, the effect of productivity shocks on debt levels is ambiguous.[30] On the one hand, when balance sheets strengthen following a positive productivity shock, firms' borrowing constraints are relaxed, and to the extent that this constraint was initially binding, they will find it profitable to increase borrowing to fund investment (as in, e.g., Kiyotaki and Moore, 1997). Under these circumstances, positive productivity shocks will be correlated with higher debt levels. On the other hand, if external finance is sufficiently costly—i.e., the external finance premium is high—and borrowing constraints are not binding, firms may find it useful to use internal funds and rely less on debt, either by borrowing smaller amounts or by repaying liabilities. In particular, when the external finance premium is high, firms will use proceeds of exogenous productivity shocks to both undertake investment as well as pay down debt (in doing so, equating the marginal return of investment to the external finance premium).

[30] This ambiguity extends to the effect of shocks on loan to value ratios as well.

Under these circumstances, debt levels will *decline* following positive productivity shocks.[31]

We empirically examine the effect of productivity shocks on debt levels by estimating our baseline regression using total farm debt and farm real estate debt as dependent variables. The results are given in Table 9. Column (1) estimates the regression using total agricultural debt as the dependent variable, while Column (2) uses agricultural real estate debt as the dependent variable. For total agricultural debt, the coefficient for contemporaneous *July Temp* is negative and significant, while the coefficient for squared *July Temp* is positive and significant. Thus, following a positive temperature shock, farmers decrease debt, and following a negative temperature shock they increase it. The effect is persistent for one lag, as lagged temperature is negative and significant while lagged squared temperature is positive (though marginally insignificant). For farm real estate debt in Column (2), the signs of the coefficients are similar, but they are insignificant.

Columns (3) and (4) of Table 9 re-estimate regression (1) for the period of the farm debt crisis, a period of financial distress and depressed net worth, as previously discussed. Consistent with the results using the full sample, during the farm debt crisis, farmers also decrease net debt holdings in response to a positive temperature shock, but in line with the predictions of financial accelerator models, the magnitude of the effect of temperature on debt is considerably larger. Further, in contrast to results from the full sample, the coefficient on real estate debt is now significant. Finally, temperature shocks persist for a longer period of time, with effects significant up to two years after the initial shock.

[31] Indeed, in a Kiyotaki and Moore (1997) model where production exhibits diminishing marginal returns, debt levels can be decreasing in productivity shocks.

3.7 Effect of Temperature Shocks in the Period Post-1990

As a final test, we analyze the effect of weather shocks in the sample period post-1990. During this period, two important changes occurred which in the context of a financial accelerator model would predict a reduced impact of weather shocks on subsequent productivity and farmland values. First, beginning in the 1990s, larger farming corporations began to exhibit a more dominant role within the industry (Sumner, 2014). Since these firms are arguably less constrained than smaller (private or family owned) farms, we predict that the effect of weather shocks post 1990 will be diminished. Further, large farming corporations caused markets for farmland to be less localized: potential buyers of land need not have been neighboring farms but could also be larger firms with geographically dispersed operations. Past local weather conditions would therefore have a smaller impact on the liquidity available to potential land purchasers, and hence local weather variation would be predicted to have a smaller effect on the demand for and price of land.

Beyond the rise of large farming corporations, the second important change to occur during the 1990s was the increased use of crop insurance. Crop insurance offered by both the U.S. government and private insurers allowed farmers to protect themselves against shortfalls in either crop revenue or crop yields due to weather fluctuations.[32] The use of insurance became widespread starting in the mid-1990s after the Federal Crop Insurance Reform Act of 1994 expanded federal subsidies for crop insurance (Glauber, 2013). The development of crop insurance markets—both federal and private—would naturally make local weather variation less important in determining local farm liquidity, investment, and land prices.[33]

The reduction in financial constraints due to the increased role of farming corporations

[32] See also Karlan et al. (2014) for evidence on the effects of crop insurance provision on agricultural investment.
[33] Indeed, hedging within a Kiyotaki and Moore (1997) framework eliminates acceleration effects.

and the increased usage of crop insurance would both predict a muted effect of weather shocks on future productivity and land values in the latter part of the sample period. To test this prediction, Table 10 reruns our baseline specification during the sample period post-1990 and reports the results of the effects of weather shocks on both corn yields and land values. As predicted, while we continue to find a contemporaneous effect of July temperature on yields, we do not find persistence.[34] Further, as hypothesized, there is no relation, contemporaneous or otherwise, between weather shocks and land values post-1990.

3.8 Insider Econometrics

To obtain a first-hand understanding of the importance of financial constraints in the intertemporal effect of productivity shocks, we interviewed directors and senior executives of lending institutions providing credit to farmers.[35] [36] Apart from having a working knowledge of the agricultural sector through their lending activities, many of the directors own large farms themselves. The interviews revealed two main findings. First, interviewees stated that bad weather during one growing season does not noticeably affect soil quality and that three to four years of hot temperature would be necessary before any noticeable effect on soil nutrients would arise. The participants also added that flooding was of far greater importance for soil quality, and even in that regard, soil nutrients begin to run off only when land is waterlogged for a prolonged period of time. The interviews also confirmed that cash constraints of local farmers, and in particular constraints that arise from poor crop yields, affect both farmland values as well as farm

[34] Weather shocks will clearly continue to affect contemporaneous yields even in the complete absence of financial frictions.
[35] We interviewed 26 directors and senior executives of the Farm Credit System—a $248 billion nationwide network of agricultural lending institutions in the United States. This credit system serves as one of the most important sources of credit to farmers, providing more than one third of total agricultural credit in the U.S.
[36] See Ichniowski and Shaw (2013) for pioneering use of "Insider Econometrics," a methodology that involves field interviews in combination with data analysis.

investment. Respondents observed that when farmers' cash position deteriorates, demand for farmland is suppressed. However, the participants also added that the development of crop insurance helped attenuate the effect of adverse weather shocks on farm balance sheets.

4 Conclusion

In this paper, we examine the amplification and propagation of economic shocks, testing key features of financial accelerator models (e.g., Bernanke and Gertler, 1989, and Kiyotaki and Moore, 1997). In order to do so, we construct a novel database in the agricultural industry and use weather shocks as a source of exogenous productivity shocks. We then examine the relation between past weather shocks and farm productivity, land values, debt, and investment.

We find that temporary temperature shocks have persistent effects on productivity and farmland values. The effects are economically significant and persist up to two years following the shock. In addition, during periods of financial market disruption, we find that the effects are substantially larger and longer-lasting. Overall, our study provides evidence in support of financial accelerator models: in the presence of financial frictions, temporary shocks that affect firm balance sheets create a dynamic feedback effect that generates persistence and amplification of shocks.

Our approach highlights the potential value of focusing on micro-level data within a particular industry—in contrast to aggregate data—to understand and quantify financial acceleration effects. Our results are directly applicable to the large agricultural sector in the world economy, and particularly so in developing countries where financial constraints are generally larger. However, we expect the results to be relevant to other industries where financial constraints play an important role.

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Table 1: Summary Statistics

This table provides summary statistics for the key variables. All variables are yearly county-level averages. $Corn\,Yield$ is defined as bushels of corn produced per acre of harvested land. $Land\,Value$ is the dollar value of farmland per acre. $Income$ is county income per capita, in thousands of dollars. $July\,Temp$ is the average temperature in July, recorded in Fahrenheit. $Permeability$ is a measure of soil permeability. $K\,factor$ represents the soil erodability factor. $Moisture$ is the soil moisture holding capacity. $Ag\,Debt$ is defined as total agricultural debt issued by banks in the given county, in thousands of dollars. $RE\,Debt$ is defined as total real estate debt secured by farmland issued by banks in the given county, in thousands of dollars, and is winsorized at the 1% level. The data for $Corn\,Yield$, $Land\,Value$, and $July\,Temp$ run from 1950 to 2010. The data for $Income\,Capita$ are from 1959 and 1969 to 2010. $Permeability$, $K\,factor$, and $Moisture$ are measured at 5-year intervals from 1978 to 2002. $Ag\,Debt$ and $RE\,Debt$ run from 1959 to 2010. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars.

Variable	# Obs	Mean	Std. Dev.	Within SD	Between SD	p25	Median	p75
$July\,Temp$	6,032	73.970	2.869	2.552	1.318	72.022	73.985	75.876
$Corn\,Yield$	6,032	106.924	39.901	39.258	7.147	74.100	105.600	136.500
$Land\,Value$	6,032	2,776.79	1,380.75	1,193.833	696.459	1,875.89	2,426.00	3,220.64
$Ag\,Debt$	5,077	81,222.52	65,445.59	47,101.85	45,614.66	43,477.71	68,951.24	100,670.90
$RE\,Debt$	5,077	21,176.86	28,653.40	25,427.78	13,249.68	6,364.55	12,521.47	25,116.52
$Income$	4,250	27.429	6.372	5.957	2.270	23.415	26.643	31.143
$Permeability$	198	1.339	0.216	0.012	0.219	1.241	1.313	1.444
$K\,factor$	198	0.294	0.032	0.001	0.032	0.262	0.303	0.322
$Moisture$	198	0.208	0.008	0.000	0.008	0.204	0.208	0.213

Table 2: Temperature Shocks on Corn Yields

This table provides regression results for the effects of temperature shocks on corn yields. All variables represent county-level values in the indicated year. $CornYield$ is defined as bushels of corn produced per acre of harvested land. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. Standard errors are given in parentheses, and are either robust and clustered at the county level, or corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. Results are run from 1950 to 2010.

Dependent Variable: $\log(CornYield)_t$

	(1)	(2)	(3)	(4)	(5)
$(JulyTemp)_t$	6.334***	6.144***	6.028***	6.097***	6.028***
	(0.913)	(0.901)	(0.897)	(0.871)	(0.361)
$(JulyTemp)^2_t$	-0.045***	-0.044***	-0.044***	-0.044***	-0.044***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)
$(JulyTemp)_{t-1}$		1.859***	1.822**	1.768**	1.822***
		(0.710)	(0.714)	(0.734)	(0.325)
$(JulyTemp)^2_{t-1}$		-0.012**	-0.012**	-0.012**	-0.012***
		(0.005)	(0.005)	(0.005)	(0.002)
$(JulyTemp)_{t-2}$			0.682	0.626	0.682***
			(0.646)	(0.659)	(0.256)
$(JulyTemp)^2_{t-2}$			-0.004	-0.004	-0.004**
			(0.004)	(0.004)	(0.002)
$(JulyTemp)_{t-3}$				0.231	
				(0.784)	
$(JulyTemp)^2_{t-3}$				-0.001	
				(0.005)	
Standard Errors	Spatial	Spatial	Spatial	Spatial	Robust
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.915	0.911	0.906	0.907	0.906
Observations	6,032	5,926	5,820	5,714	5,820

Table 3: Temperature Shocks on Land Values

This table provides regression results for the effects of temperature shocks on farm land values. All variables represent county-level values in the indicated year. $LandValue$ is the dollar value of farmland per acre. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are either robust and clustered at the county level, or corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. Results are run from 1950 to 2010.

Dependent Variable: $\log(LandValue)_t$

	(1)	(2)	(3)	(4)	(5)
$(JulyTemp)_t$	0.586*	0.478	0.300	0.304	0.300**
	(0.355)	(0.361)	(0.361)	(0.357)	(0.125)
$(JulyTemp)^2_t$	-0.004	-0.003	-0.002	-0.002	-0.002**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
$(JulyTemp)_{t-1}$		0.819**	0.710**	0.587*	0.710***
		(0.352)	(0.352)	(0.353)	(0.108)
$(JulyTemp)^2_{t-1}$		-0.005**	-0.005*	-0.004	-0.005***
		(0.002)	(0.002)	(0.002)	(0.001)
$(JulyTemp)_{t-2}$			0.821**	0.715**	0.821***
			(0.345)	(0.347)	(0.132)
$(JulyTemp)^2_{t-2}$			-0.005**	-0.005**	-0.005***
			(0.002)	(0.002)	(0.001)
$(JulyTemp)_{t-3}$				0.508	
				(0.320)	
$(JulyTemp)^2_{t-3}$				-0.003	
				(0.002)	
Standard Errors	Spatial	Spatial	Spatial	Spatial	Robust
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.982	0.983	0.983	0.984	0.983
Observations	6,032	5,926	5,820	5,714	5,820

Table 4: Temperature Effects, Interaction with Financial Constraints

This table provides regression results for the effects of temperature shocks on corn yields and land values, and the interaction with financial constraints as measured by county income per capita. All variables represent county-level values in the indicated year. $CornYield$ is defined as bushels of corn produced per acre of harvested land. $LandValue$ is the dollar value of farmland per acre. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. $Income$ is county income per capita, in thousands of dollars. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are either robust and clustered at the county level, or corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include $(Income)_{t-1}$, $(Income)_{t-2}$, and an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. Results are run for 1959, and 1969 to 2010.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\log(CornYield)_t$			$\log(LandValue)_t$		
$(Income)_t$	13.321**	13.651**	13.651***	2.635	3.993*	3.993***
	(6.204)	(6.182)	(2.678)	(2.173)	(2.128)	(1.091)
$(JulyTemp)_t$	17.173***	17.378***	17.378***	2.485	3.520**	3.520***
	(5.268)	(5.253)	(2.139)	(1.655)	(1.623)	(0.789)
$(JulyTemp)_t \times (Income)_t$	-0.365**	-0.375**	-0.375***	-0.075	-0.112*	-0.112***
	(0.171)	(0.171)	(0.074)	(0.059)	(0.057)	(0.029)
$(JulyTemp)^2_t$	-0.121***	-0.123***	-0.123***	-0.017	-0.024**	-0.024***
	(0.036)	(0.036)	(0.015)	(0.011)	(0.011)	(0.005)
$(JulyTemp)^2_t \times (Income)_t$	0.003**	0.003**	0.003***	0.001	0.001**	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$(JulyTemp)_{t-1}$	9.369***	9.204***	9.204***	3.880**	3.955**	3.955***
	(3.340)	(3.253)	(1.613)	(1.595)	(1.669)	(0.826)
$(JulyTemp)_{t-1} \times (Income)_{t-1}$	-0.309**	-0.307**	-0.307***	-0.117**	-0.120**	-0.120***
	(0.125)	(0.121)	(0.063)	(0.055)	(0.057)	(0.032)
$(JulyTemp)^2_{t-1}$	-0.061***	-0.060***	-0.060***	-0.026**	-0.027**	-0.027***
	(0.022)	(0.022)	(0.011)	(0.011)	(0.011)	(0.006)
$(JulyTemp)^2_{t-1} \times (Income)_{t-1}$	0.002**	0.002**	0.002***	0.001**	0.001**	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$(JulyTemp)_{t-2}$		-0.683	-0.683		4.434**	4.434***
		(3.200)	(1.442)		(2.095)	(1.202)
$(JulyTemp)_{t-2} \times (Income)_{t-2}$		0.043	0.043		-0.158**	-0.158***
		(0.115)	(0.055)		(0.077)	(0.045)
$(JulyTemp)^2_{t-2}$		0.005	0.005		-0.030**	-0.030***
		(0.022)	(0.010)		(0.014)	(0.008)
$(JulyTemp)^2_{t-2} \times (Income)_{t-2}$		-0.000	-0.000		0.001**	0.001***
		(0.001)	(0.000)		(0.001)	(0.000)
Standard Errors	Spatial	Spatial	Robust	Spatial	Spatial	Robust
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.853	0.854	0.854	0.986	0.986	0.986
Observations	4,045	3,939	3,939	4,045	3,939	3,939

Table 5: Temperature Shocks During the Farm Debt Crisis

This table provides regression results for the effects of temperature shocks on corn yields for the period from 1981 to 1986. All variables represent county-level values in the indicated year. $Corn\,Yield$ is defined as bushels of corn produced per acre of harvested land. $Land\,Value$ is the dollar value of farmland per acre. $July\,Temp$ is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are either robust and clustered at the county level, or corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\log(Corn\,Yield)_t$			$\log(Land\,Value)_t$		
$(July\,Temp)_t$	18.597***	20.241***	20.241***	1.797**	1.881**	1.881***
	(4.950)	(5.295)	(2.886)	(0.762)	(0.783)	(0.428)
$(July\,Temp)_t^2$	-0.129***	-0.140***	-0.140***	-0.012**	-0.012**	-0.012***
	(0.034)	(0.036)	(0.020)	(0.005)	(0.005)	(0.003)
$(July\,Temp)_{t-1}$	4.302**	5.672***	5.672***	1.050*	1.088*	1.088***
	(1.823)	(2.171)	(1.053)	(0.555)	(0.598)	(0.299)
$(July\,Temp)_{t-1}^2$	-0.028**	-0.037**	-0.037***	-0.007*	-0.007*	-0.007***
	(0.012)	(0.015)	(0.007)	(0.004)	(0.004)	(0.002)
$(July\,Temp)_{t-2}$		3.604*	3.604***		0.601	0.601*
		(2.022)	(1.025)		(0.667)	(0.309)
$(July\,Temp)_{t-2}^2$		-0.023*	-0.023***		-0.004	-0.004*
		(0.013)	(0.007)		(0.004)	(0.002)
Standard Errors	Spatial	Spatial	Robust	Spatial	Spatial	Robust
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.768	0.770	0.770	0.995	0.995	0.995
Observations	594	594	594	594	594	594

Table 6: Instrumental Variable Estimates

This table provides instrumental variable estimates for corn yield and land values, instrumenting for past yields using past temperature. All variables represent county-level values in the indicated year. $CornYield$ is defined as bushels of corn produced per acre of harvested land. $LandValue$ is the dollar value of farmland per acre. $\log(\widehat{yield})$ is instrumented log corn yields. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are either robust and clustered at the county level, or corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. Results are run from 1950 to 2010.

	(1)	(2)	(3)
Dependent Variable:	$\log(CornYield)_{t-1}$	$\log(CornYield)_t$	$\log(LandValue)_t$
$\log(\widehat{yield})_{t-1}$		0.094***	0.048***
		(0.029)	(0.015)
$(JulyTemp)_t$	-0.535	6.354***	0.438***
	(0.607)	(0.278)	(0.139)
$(JulyTemp)^2_t$	0.004	-0.046***	-0.003***
	(0.004)	(0.002)	(0.001)
$(JulyTemp)_{t-1}$	5.972***		
	(0.919)		
$(JulyTemp)^2_{t-1}$	-0.043***		
	(0.006)		
$(JulyTemp)_{t-2}$	2.550***		
	(0.648)		
$(JulyTemp)^2_{t-2}$	-0.017***		
	(0.004)		
Standard Errors	Spatial	Robust	Robust
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.916	0.909	0.984
F-statistic	379.17		
Observations	5,280	5,820	5,820

Table 7: Temperature Shocks on Corn Yields, Controlling for Soil Quality

This table provides regression results for the effects of temperature shocks on corn yields, controlling for the effects on soil quality. All variables represent county-level values in the indicated year. $CornYield$ is defined as bushels of corn produced per acre of harvested land. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. $Permeability$ is a measure of soil permeability. $K\,factor$ represents the soil erodability factor. $Moisture$ is the soil moisture holding capacity. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. Results are run for every five years from 1978 to 2002.

Dependent Variable: $\log(CornYield)_t$

	(1)	(2)	(3)	(4)	(5)	(6)
$(Permeability)_t$	0.697**	-0.763				
	(0.337)	(3.487)				
$(K\,factor)_t$			-6.312***	-6.928		
			(1.836)	(99.073)		
$(Moisture)_t$					-0.132	21.160
					(6.368)	(133.080)
$(JulyTemp)_t$	4.446***	4.618***	4.336***	4.611***	4.510***	4.612***
	(1.023)	(0.905)	(0.955)	(0.917)	(0.951)	(0.905)
$(JulyTemp)_t^2$	-0.032***	-0.033***	-0.031***	-0.033***	-0.032***	-0.033***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
$(JulyTemp)_{t-1}$	3.853***	2.108*	4.163***	2.110*	4.194***	2.132*
	(1.306)	(1.167)	(1.216)	(1.170)	(1.277)	(1.172)
$(JulyTemp)_{t-1}^2$	-0.026***	-0.016**	-0.028***	-0.016**	-0.028***	-0.016**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Standard Errors	Spatial	Spatial	Spatial	Spatial	Spatial	Spatial
County FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.767	0.866	0.771	0.866	0.758	0.866
Observations	198	198	198	198	198	198

Table 8: Effect of Temperature Shocks on Machinery Investment

This table provides regression results for the effects of temperature shocks on the value of machinery purchases. All variables represent county-level values in the indicated year. $Mach\,Purchase$ is the total value of machinery purchases. $July\,Temp$ is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. The results run from 1995 to 2010.

	(1)	(2)	(3)
Dependent Variable:	$(Mach\,Purchase)_t$	$(Mach\,Purchase)_t$	$(Mach\,Purchase)_t$
$(July\,Temp)_t$	3.996*	4.404*	4.225*
	(2.414)	(2.396)	(2.370)
$(July\,Temp)^2_t$	-0.028*	-0.031*	-0.030*
	(0.016)	(0.016)	(0.016)
$(July\,Temp)_{t-1}$		4.561*	4.523*
		(2.561)	(2.572)
$(July\,Temp)^2_{t-1}$		-0.031*	-0.031*
		(0.017)	(0.018)
$(July\,Temp)_{t-2}$			-0.679
			(2.302)
$(July\,Temp)^2_{t-2}$			0.005
			(0.016)
Standard Errors	Spatial	Spatial	Spatial
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.626	0.626	0.624
Observations	1,575	1,569	1,562

Table 9: Temperature Shocks on Debt Levels

This table provides regression results for the effects of temperature shocks on debt levels. All variables represent county-level values in the indicated year. *Ag Debt* is defined as total agricultural debt issued by banks in the given county. *RE Debt* is defined as total real estate debt secured by farmland issued by banks in the given county, and is winsorized at the 1% level. *July Temp* is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation. Columns (1) and (2) give results for 1959 to 2010, while columns (3) and (4) give results for 1981 to 1986.

	Full Sample		Farm Debt Crisis	
	(1)	(2)	(3)	(4)
Dependent Variable:	$\log(Ag\,Debt)_t$	$\log(RE\,Debt)_t$	$\log(Ag\,Debt)_t$	$\log(RE\,Debt)_t$
$(July\,Temp)_t$	-1.753*	-2.056	-4.565***	-7.024**
	(0.986)	(1.402)	(1.338)	(2.980)
$(July\,Temp)_t^2$	0.013**	0.014	0.031***	0.044**
	(0.007)	(0.009)	(0.009)	(0.020)
$(July\,Temp)_{t-1}$	-1.457	-1.007	-6.083***	-8.833**
	(0.964)	(1.451)	(1.700)	(3.530)
$(July\,Temp)_{t-1}^2$	0.011*	0.007	0.041***	0.057**
	(0.006)	(0.010)	(0.011)	(0.024)
$(July\,Temp)_{t-2}$	-0.145	-0.116	-5.336***	-6.825**
	(0.982)	(1.635)	(1.550)	(3.303)
$(July\,Temp)_{t-2}^2$	0.003	0.001	0.035***	0.043*
	(0.007)	(0.011)	(0.010)	(0.022)
Standard Errors	Spatial	Spatial	Spatial	Spatial
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.759	0.819	0.934	0.836
Observations	5,063	5,062	594	594

Table 10: Effects Post-1990s

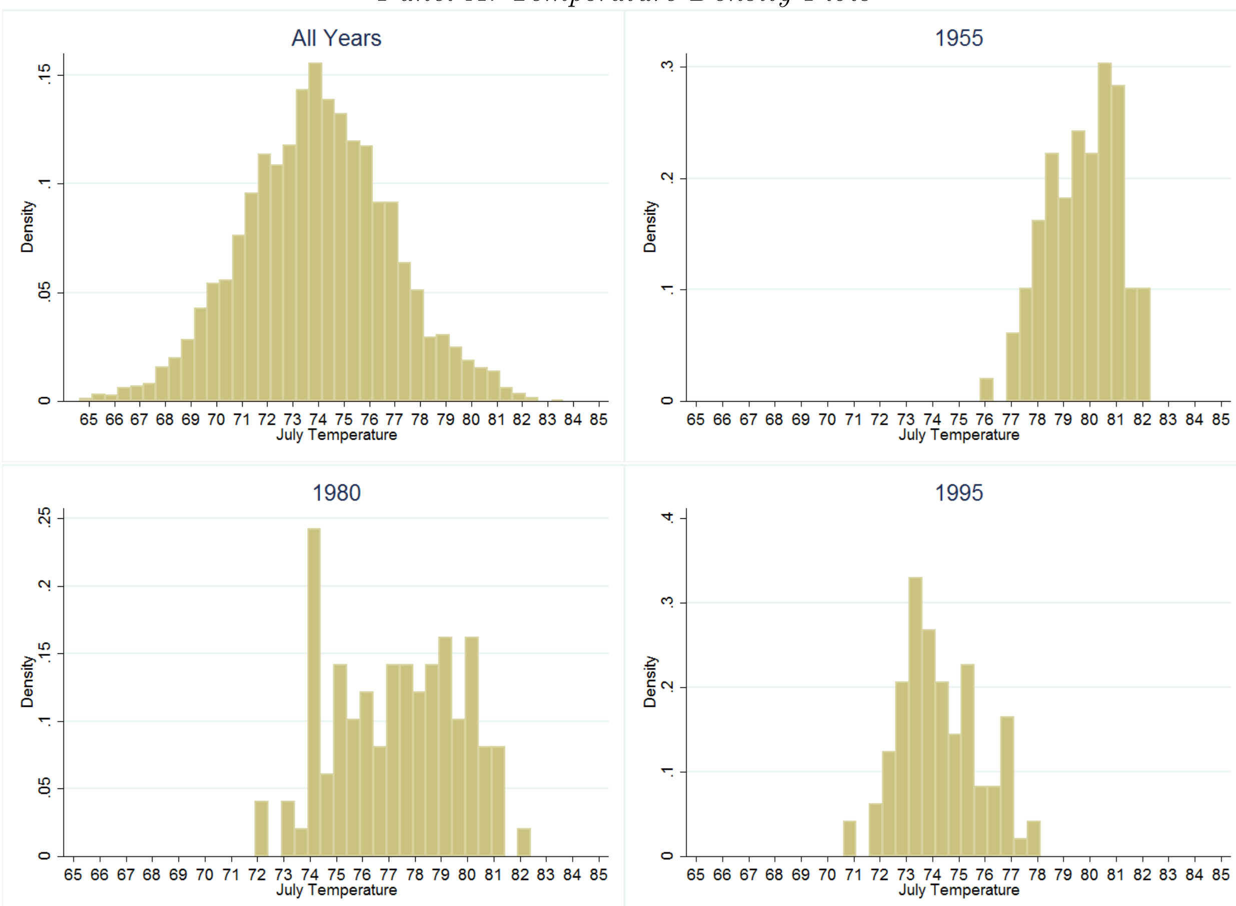
This table provides results of the effects in the period post-1990. The sample period runs from 1990 to 2010. All variables represent county-level values in the indicated year. $CornYield$ is defined as bushels of corn produced per acre of harvested land. $LandValue$ is the dollar value of farmland per acre. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation.

	(1)	(2)	(3)	(4)
Dependent Variable:	$\log(CornYield)_t$		$\log(LandValue)_t$	
$(JulyTemp)_t$	4.820***	4.780***	-0.529	-0.520
	(0.711)	(0.706)	(0.372)	(0.370)
$(JulyTemp)^2_t$	-0.034***	-0.034***	0.003	0.003
	(0.005)	(0.005)	(0.003)	(0.003)
$(JulyTemp)_{t-1}$		-1.093		-0.267
		(1.236)		(0.364)
$(JulyTemp)^2_{t-1}$		0.008		0.002
		(0.008)		(0.002)
Standard Errors	Spatial	Spatial	Spatial	Spatial
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.845	0.846	0.987	0.987
Observations	2,072	2,065	2,072	2,065

Figure 1: Temperature Density Plots

Panel A shows density plots for temperature. The first graph indicates the distribution of temperature for all county-years in the sample. The second graph indicates the distribution of temperature for counties in 1955. The third graph indicates the distribution of temperature for counties in 1980. The fourth graph indicates the distribution of temperature for counties in 1995. Panel B shows de-meaned density plots for temperature. The left graph shows the distribution of temperature in excess of each county's mean temperature for all county-years in the sample. The right graph shows the distribution of temperature in excess of each year's mean temperature for all county-years in the sample. All temperatures are in degrees Fahrenheit.

Panel A: Temperature Density Plots



Panel B: De-meaned Temperature Density Plots

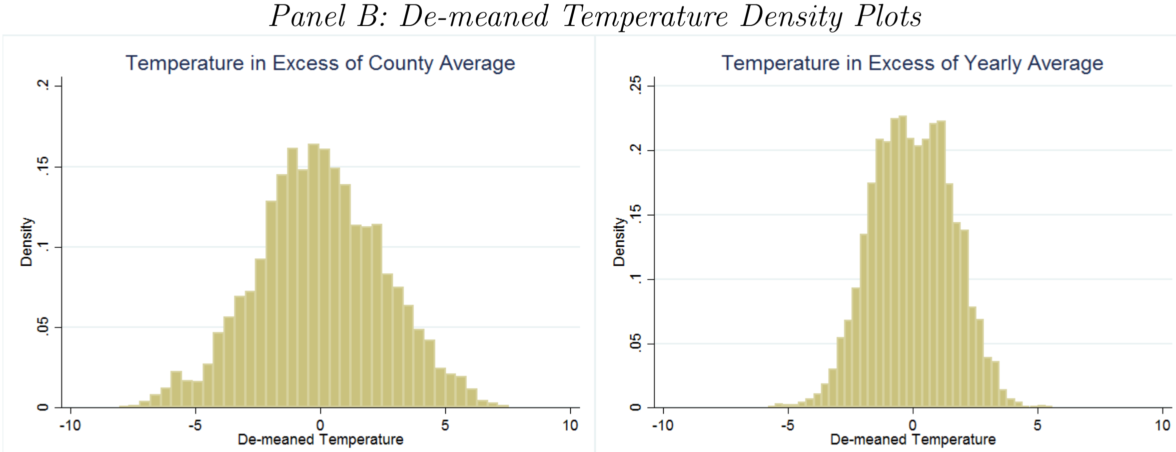
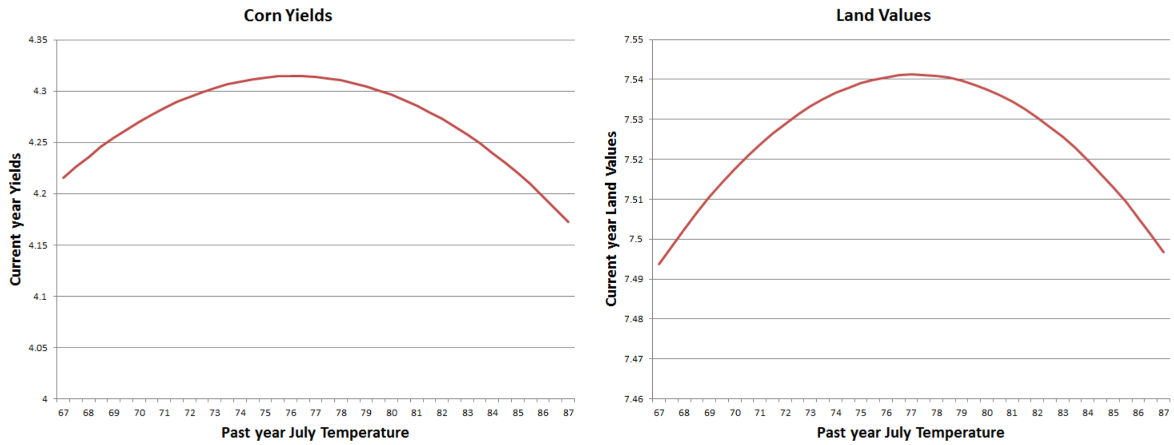


Figure 2: Effect of Temperature on Corn Yields and Land Values

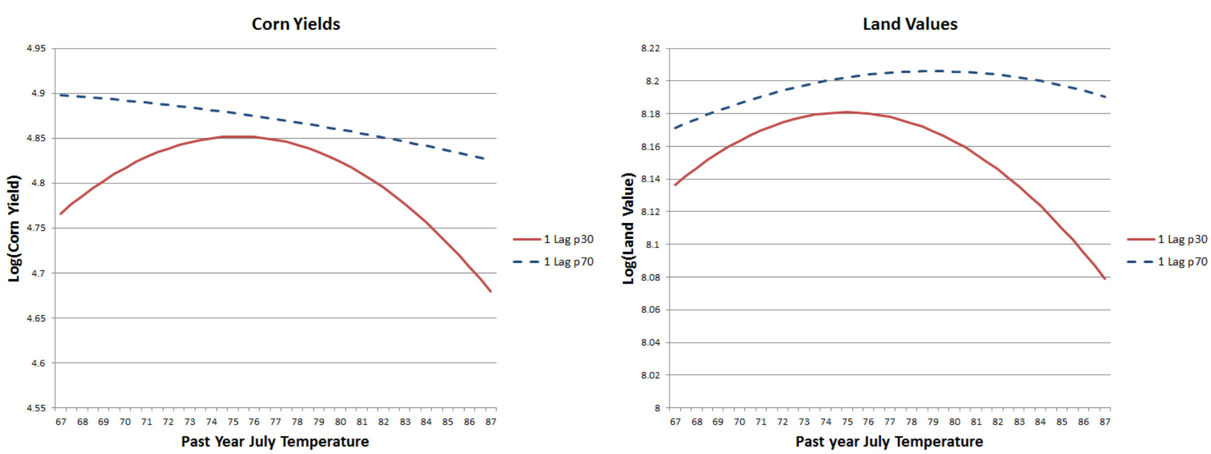
Panel A: Past Temperatures on Yields and Land Values

The left curve shows the effect of changing July temperature from one year prior on current corn yields, while the right curve shows the effect on land values. Temperature is measured in degrees Fahrenheit. Corn yields are measured in log bushels per acre, and land values are measured in log dollars per acre (in real 2010 dollars).



Panel B: Past Temperatures on Yields and Land Values at Different Levels of Income

The left figure depicts the effect of July temperature on Iowa corn yields at different levels of income per capita, while the right figure depicts the effect for land values. The solid red line shows the effect of changing July temperature from one year prior on current yields or land values, for counties at the 30th percentile of income per capita. The long-dashed blue line shows the effect of changing July temperature from one year prior on current yields or land values, for counties at the 70th percentile of income per capita. Temperature is measured in degrees Fahrenheit. Corn yields are measured in log bushels per acre, and land values are measured in log dollars per acre (in real 2010 dollars).



Appendix: For Online Publication

Table A1: Robustness—Placebo Regressions

This table provides placebo regression results. All variables represent county-level values in the indicated year, and results run from 1950 to 2010. $CornYield$ is defined as bushels of corn produced per acre of harvested land. $LandValue$ is the dollar value of farmland per acre. $JulyTemp$ is the average temperature in July, recorded in Fahrenheit. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). Reported coefficient estimates are scaled by a factor of 10 in order to ease interpretation.

	(1)	(2)
Dependent Variable:	$\log(CornYield)_t$	$\log(LandValue)_t$
$(JulyTemp)_{t+1}$	-0.535	-0.132
	(0.607)	(0.367)
$(JulyTemp)^2_{t+1}$	0.004	0.001
	(0.004)	(0.002)
$(JulyTemp)_t$	5.972***	0.457
	(0.919)	(0.364)
$(JulyTemp)^2_t$	-0.043***	-0.003
	(0.006)	(0.002)
$(JulyTemp)_{t-1}$	2.550***	0.880**
	(0.648)	(0.363)
$(JulyTemp)^2_{t-1}$	-0.017***	-0.006**
	(0.004)	(0.002)
Standard Errors	Spatial	Spatial
County and Year Fixed Effects	Yes	Yes
Adjusted R^2	0.913	0.982
Observations	5,820	5,820

Figure A1: Time-series of Yields, Land Values, and Debt

All graphs are time-series averages (across all counties for each year). Corn yield is measured in bushels per acre. Land values are given in dollars per acre of farmland. Total agricultural debt is in thousands of dollars. All dollar amounts are scaled by the Consumer Price Index (CPI), and are reported in real 2010 dollars.