The Effect of Cash Injections: Evidence from the 1980s Farm Debt Crisis*

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Abstract

What is the effect of cash injections during financial crises? Exploiting county-level variation arising from random weather shocks during the 1980s Farm Debt Crisis, we analyze and measure the effect of local weather-driven cash flow shocks on the real and financial sector. We show that such cash flow shocks have significant impact on a host of economic outcomes, including land values, loan delinquency rates, the probability of bank failure, employment, and wages. Estimates of the effect of local cash flow shocks on county income levels during the financial crisis yield a multiplier of 1.63.

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1 Introduction

A large theoretical literature exists showing that in the presence of financial frictions, weak firm balance sheets detrimentally affect economic activity (see e.g., Bernanke and Gertler 1989, 1995; Shleifer and Vishny 1992; Gertler and Gilchrist 1994; and Kiyotaki and Moore 1997). Strengthening firm balance sheets during a financial crisis is thus a much discussed and debated question.[1] By reducing financial frictions, such interventions may increase investment, support lending, raise employment, and mitigate the severity of a financial crisis.

Estimating the economic effect of interventions meant to strengthen firm balance sheets during a financial crisis is a difficult task – the timing and strength of such interventions are likely to be endogenous and driven by the severity of the crisis itself. Since interventions generally occur in response to severe crises, a simple correlation would suggest, likely erroneously, that such interventions have detrimental effects on the economy.

To understand the effect of interventions that strengthen firm balance sheets during financial crises, we focus on the farm debt crisis of the 1980s. Assembling a yearly, county-level dataset of weather and farm data in Iowa, our identification strategy relies on exploiting variation arising from random weather shocks. As a large literature in agronomics shows, weather shocks affect crop yields and hence farm cash flow (see, e.g., Deschenes and Greenstone 2007, Schlenker and Roberts 2009). Geographic variation in weather realizations thus provide plausibly exogenous variation in local cash flow and are akin to cash injections of differing magnitudes to farms operating across different counties. In this paper, we analyze and measure the effect of such exogenous cash injections during a financial crisis on both the real and financial sector.

[1] See e.g. the substantial debate during the 2008-2009 financial crisis regarding the effectiveness of stimulus bills such as the Economic Stimulus Act of 2008 and the American Economy and Reinvestment Act of 2009, which, among other provisions, reduced firms' tax obligations and in so doing strengthened real sector balance sheets.

Spanning the period 1981-1987, the Farm Debt Crisis resembled in many ways the financial crisis of 2008-2009, with agricultural land prices and farm debt – much of it collateralized by land – increasing substantially prior to the crisis onset. Subsequently, during the crisis itself, land prices in the U.S. corn-belt plummeted by nearly 50 percent. The farming sector saw severe deleveraging – total agricultural debt declining by 29 percent from 1984 to 1988 – and experienced substantial disruptions with numerous farm bankruptcies as well as agricultural bank failures throughout the period.[2]

As a first step in our empirical analysis, we confirm that county-level weather variation is related to farm yields in our data. Focusing on corn production in Iowa, we measure how temporary shocks in weather during the corn growing season affect yields. Consistent with a large literature in agronomics, we find that corn is highly sensitive to small changes in temperature, with even a few additional hot days during the growing season reducing annual corn yields substantially.

Since local weather affects yields, weather shocks provide exogenous variation in local cash flows and farms' net worth during the debt crisis. We exploit this variation in our empirical strategy by relating weather-driven cash flow shocks to a host of real and financial variables – both during the farm debt crisis as well as outside of it. Our analysis focuses on land markets, the propagation of shocks into the financial sector, and on labor markets. While during normal times, firms should be able to smooth temporary shocks, in financial crises and other periods of large financial frictions, such smoothing is difficult as external finance is often prohibitively costly or unavailable.[3] An inability to smooth shocks during a crisis is predicted, therefore, to translate to a host of market outcomes, both real and financial. Consistent with financial accelerator theories, our results show that weather-driven cash injections during the crisis positively affect land markets, the financial sector, and labor markets

[2] For an analysis of the farm debt crisis see e.g. Calomiris, Hubbard, and Stock (1986) and Barnett (2000).

[3] Brunnermeier and Sannikov (2014) provide a model consisting of two regimes – crisis and non-crisis – in which, in the former, small shocks are amplified, while in the latter these shocks are absorbed by agents. For example, firms may be able to draw on additional credit lines during normal times in order to absorb such shocks (see Brown, Gustafson, and Ivanov, 2017, for evidence).

in an economically meaningful manner, and ultimately translate into increases in county per-capita income.

We start by examining the effect of weather shocks on agricultural land prices. We expect that during a financial crisis, increases in cash available to firms will support asset prices by mitigating fire sales. When financial frictions are high, asset prices will be affected by cash-in-the-market pricing, as economic agents cannot raise external finance to bring prices to fundamental value (Allen and Gale 1994, 1998; Shleifer and Vishny 1992; Kiyotaki and Moore 1997).[4]

Consistent with cash-in-the-market pricing, we show that weather-induced cash flow injections do indeed increase land prices. Since our specifications include both year and county fixed effects, our identification strategy is driven by comparing, within a given year, counties that received differential weather shocks, as compared to their sample mean. We find that counties that received a positive cash flow injection – driven by relatively good weather – exhibit higher land values than counties that receive a negative cash flow shock – driven by a few additional days of high temperature weather during the growing season. Instrumenting for county-level crop yields with our weather shock variable, we find an elasticity of land prices to yields during the farm debt crisis of 0.34. As a placebo test, we rerun our analysis on the period outside of the farm debt crisis and find no statistically significant relation between land values and weather shocks. To our knowledge, this is the first study that provides causal evidence of cash-in-the-market pricing.

Because weather shocks affect both farm income and land values, our empirical methodology cannot isolate separately the impact of variation in income and land values on the additional economic

[4] As in all models of cash-in-the-market pricing, an implicit assumption here is that asset markets are at least partially segmented in that capital cannot flow seamlessly from one market to the other (see e.g. Shleifer and Vishny 1992; Allen and Gale 1994, 1998; Duffie 2010). The market for agricultural land is thought to fit this assumption well, as land is often purchased by neighboring local farms—a hypothesis we confirm below with a hand-gathered, micro-level dataset of land transaction records. See also Chaney, Sraer, and Thesmar (2012) for the impact of changes in real estate prices on corporate investment via a collateral channel.

outcomes analyzed below. Indeed, one of the key insights of Kiyotaki and Moore (1997) is that the income channel and the asset value channel (i.e. land values in the present context) are *inherently and endogenously* intertwined, with exogenous cash flow shocks affecting equilibrium asset values and asset values further affecting cash flows through their impact on collateral constraints. In discussing the impact of exogenous weather variation, we thus refer to the impact of weather-driven cash flow shocks, which should be understood as affecting farm net worth, both directly through the income channel (through the impact on yields) as well as indirectly through the associated change in land values.

We continue our analysis by examining how weather-driven cash flow shocks propagate into the financial sector. We first show that during the crisis, counties that experience reduced crop yields due to bad weather shocks exhibit higher agricultural loan delinquencies: as would be predicted, farms in these counties find it more difficult to repay their obligations. We then show that these county level cash injections reduce the probability of local bank failure during the crisis. The effect is economically significant, with a 10 percent drop in crop yields increasing the probability of a county bank failure by 3.2 percent.[5] Thus, weather-driven cash flow shocks during the crisis create long lasting effects in the financial sector.

We then turn to the effect of cash flow injections during crises on labor markets. We begin by focusing on the labor market in the agricultural sector and then examine spillovers into labor markets in other sectors. The results show that counties that experience a negative cash flow shock during the crisis exhibit lower agricultural employment rates as well as a reduction in average county agricultural wages, consistent with a reduction in farms' labor demand.[6] During the debt crisis when financial

[5] As a placebo test, we rerun the analysis relating cash flow shocks to bank failures and loan delinquencies outside of the crisis. As expected, we find no significant relations.
[6] We confirm that outside of the crisis period, weather driven cash flow shocks have no effect on employment or on average wages in the agricultural sector.

frictions are high, lower firm net worth thus translate into labor market disruptions and decreased employment. We rerun the analysis outside of the farm debt crisis, and show that weather-driven cash flow shocks do not affect employment and wages during this time period, consistent with firms' greater ability to smooth shocks when financial frictions and the cost of external finance are lower.

We next examine labor market spillover effects of cash flow shocks in the agriculture sector into the service sector.[7] We hypothesize that during the debt crisis disruptions in agricultural labor markets following cash flow shocks will spill over into other labor markets. This is indeed what the data show. During the debt crisis, county-level weather-driven negative cash flow shocks in the *agricultural* sector are related to employment increases, as well as average wage decreases, in the local *service* sector. During the crisis, a negative cash flow shock in agriculture appears, therefore, to increase labor supply in the service sector, with workers reallocating from agriculture to services.

We continue by examining whether these labor market spillovers in the service sector depend on the share of agriculture in the local economy. Our hypothesis is that when the agriculture sector is large within a given county, reductions in agricultural employment following a negative cash flow shock will reduce local demand, and hence employment, in the service sector.[8] Running interaction specifications conditioning on the share of agricultural income within the county, we find results consistent with this demand channel: in counties where farming is more dominant, during the farm debt crisis negative cash flow shocks in agriculture have a negative effect on employment within the service sector. Firms' inability to smooth cash flow shocks during the debt crisis is thus transmitted to other industries located within the same area, as employees are dislocated within the economy.

Overall, our results regarding the impact of external shocks during the debt crisis are consistent with the amplifying effect of financial frictions and models of the financial accelerator. As further

[7] Examining wages and employment in manufacturing, we do not find any significant effects.
[8] See Mian and Sufi (2014) for an examination of the relation between local household demand shocks and employment within the tradable and non-tradable sectors during the 2008-2009 recession.

evidence in support of this financial-friction channel, we also exploit cross-sectional variation in local banking market characteristics. In particular, we show that during the debt crisis, the relation between weather shocks and the various outcome variables described above is stronger in counties with higher funding constraints in the banking sector as measured by loan-to-deposit ratios. Thus, for example, we find that the elasticity of land values to yields is approximately 40 percent greater in high Loan-to-Deposit counties as compared to low Loan-to-Deposit counties.

We conclude by analyzing whether and to what extent exogenous cash flow shocks ultimately affected county-level income during the debt crisis. To this end, we calculate the local-level cash-flow to income multiplier – i.e. the increase in income associated with a dollar injection of cash flow. The results show that positive cash flow shocks during the debt crisis did indeed increase local income levels, with our estimates pointing to a multiplier of approximately 1.63. In periods outside of the debt crisis, we do not find a statistically significant relation between cash flow shocks and county income levels. The size of the cash flow to income multiplier is thus state dependent, and larger during crises.[9]

Taken together, our results show how cash injections into an economy during a debt crisis can have important effects on a host of real and financial outcomes. When firm net worth is reduced, asset prices decline, delinquency rates rise, banks are more likely to fail, labor market disruptions ensue, and income levels decline. Conversely, increased net worth during the crisis improve conditions in local land markets, financial markets, and labor markets, and ultimately raise income levels. From a policy perspective, our results thus point to the potential value of cash injections during a financial crisis that serve to strengthen firm balance sheets, thereby aiding firms in overcoming frictions in financial

[9] For a discussion of the difficulty in estimating state-dependent fiscal multipliers, see Parker (2011). Auerbach and Gorodnichenko (2012) use a smooth transition VAR to estimate fiscal multipliers over the business cycle, finding a multiplier of between 1.5 and 2 in recessions. See also Ramey and Zubairy (2014), which employs a long time series of U.S. data to estimate state-dependent fiscal multipliers, and Chodorow-Reich et al. (2012) which examines the effect of state-level fiscal policy on employment. Nakamura and Steinsson (2014) estimate government spending multipliers using variation driven by military procurement. See also the literature on fiscal policy at the zero lower bound (e.g. Krugman 1998; Eggertsson and Woodford 2003; and Christiano, Eichenbaum, and Rebelo 2011).

markets.

The paper proceeds as follows. The next section presents the empirical strategy, data, and a description of the farm debt crisis, along with the summary statistics. Section 3 presents the empirical analysis: Section 3.1 confirms that weather shocks affect crop yields; Section 3.2 analyzes the effect of weather-driven county-level cash flow shocks on land markets; Section 3.3 focuses on the propagation of cash flow shocks into the banking sector; Section 3.4 analyzes the effect of cash flow shocks on labor markets, focusing on employment and wages; Section 3.5 examines how the effects differ based on heterogeneity in the degree of banking frictions; and Section 3.6 investigates the multiplier of cash flow shocks on income-per-capita. Section 4 concludes.

2 Empirical Methodology and Data

2.1 Empirical Strategy

Our empirical strategy employs idiosyncratic weather shocks and their attendant effect on agricultural growing productivity as a source of variation in local cash flow. An extensive body of literature has shown that variation in weather has a strong effect on agricultural productivity (see, e.g., Dell, Jones, and Olken 2014, for a review). This variation is plausibly exogenous to farm-level activity, certainly within the frequency we study.

The analysis focuses 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 in the state.[10] Iowa also ranks first out of all states in production of corn – an important U.S. crop whose response to temperature fluctuations is well

[10] According to the Iowa Farm Bureau, the agriculture sector accounts for $72 billion in Iowa's economy annually and creates one out of every six new jobs.

understood. Finally, agricultural data for Iowa are available at a more detailed level and for a longer time period compared to other states, allowing for a more complete time series of our empirical tests.

Our main empirical strategy uses an instrumental variable approach to relate exogenous weather-driven changes in crop yields to economic outcomes in various markets of interest: the market for land, the local financial sector, and labor markets. In doing so, we rely on an extensive prior literature in agricultural economics showing that corn is highly sensitive to variation in temperature during the growing season – the months from April through September – with even a few additional days of hot weather significantly reducing *annual* corn yields (see e.g. Schlenker and Roberts 2006, 2009). Thus, the variation exploited in our identification strategy is not periods of drought or extreme heat throughout the growing season, but rather relatively small variation in temperature across counties within a given year which generate strong negative shocks to yields. Counties that did not experience the negative weather shock exogenously have greater cash flows, on average, than counties which did. It is this variation – i.e. the relative increase in cash flows between counties which did and did not experience a negative weather shock – that drives our identification strategy.

It is important to note that our empirical methodology cannot differentiate whether the effect of weather shocks on the various real and financial outcomes analyzed is driven solely by the impact on farm income (stemming from the impact on yields) or alternatively, is driven, at least in part, by the impact weather shocks have on farm land values. Indeed, weather shocks are found in our analysis to shift both income and land values, and so the relative importance of each channel in affecting the economic variables of interests is not identifiable. In line with this, one of the key insights of Kiyotaki and Moore (1997) is that the income and asset value channels are endogenously intertwined, with exogenous cash flow shocks affecting equilibrium asset values, and changes in asset values further influencing cash flows via their impact on collateral constraints. As previously noted, when discussing the impact of weather variation, we therefore refer to the impact of weather-driven cash flow shocks, which should be understood as affecting farm net worth, both through the income channel (via the impact on yields) as well as through the associated change in land values.

We measure county-level annual exposure to harmful temperature using the cumulative number of days in the growing season with average daily temperature above 83 degrees Fahrenheit (83°F), a threshold corresponding to that identified in the literature.[11] Annual county-level corn yields are instrumented in a first stage regression with the days-above-83°F weather shock variable – i.e. the number of days in the growing season with temperature above 83°F – and in a second stage regression various variables of interest (described below) are related to the instrumented yields. The first-stage regression in our analysis is thus given by:

$$\log\left(\mathit{Corn\ Yield}_{i,t}\right) = \beta_0 + \beta_1 (\mathit{Days\ Above\ 83})_{i,t} + \delta_t + \gamma_i + \varepsilon_{i,t}\,, \tag{1}$$

where $\mathit{Corn\ Yield}_{i,t}$ is annual county-level bushels per acre in county i in year t, and *Days Above 83* is the annual number of days in the corn growing season in each county which have an average temperature above 83°F. Regression (1) is run at the county-year level and includes year fixed effects, δ_t, as well as county fixed effects, γ_i, to absorb time-invariant omitted characteristics at the county level as well as shocks common to all counties within a given year. For ease of interpretation, we do not include rainfall in the above specifications; however, our results are robust to including precipitation during the growing season as a control.[12]

Our second-stage regression specification examines the effect of instrumented corn yields, given by (1), on various outcome variables:

[11] Schlenker and Roberts (2009) find that hot temperature is harmful to corn yields past a threshold of 28°C to 29°C (depending on the geographical region), i.e. 82.4°F to 84.2°F. They show that an additional day of weather at 40°C (104°F) instead of 29°C (84.2°F) leads to an approximately 7 percent predicted decline in *annual* yields.

[12] Robustness to controlling for precipitation is consistent with the agricultural literature's focus on temperature as the first-order weather-related determinant of yields. See for example Schlenker and Roberts (2009) which finds poor predictive power of precipitation compared to temperature when exploring interactive weather effects on corn yields.

$$Y_{i,t} = \beta_0 + \log\left(\widehat{Yield_{i,t}}\right) + \delta_t + \gamma_i + \varepsilon_{i,t}\,, \tag{2}$$

where $Y_{i,t}$ is the outcome variable of interest for county i in year t, $\log\left(\widehat{Yield_{i,t}}\right)$ is predicted log corn yield as instrumented via regression (1), δ_t are year fixed effects, and γ_i are county fixed effects.[13] The outcome variables examined are average agricultural land values, agricultural loan delinquency rates, number of bank failures, average wages, and employment, all at the county-level. The exclusion restriction underlying the identification strategy is that temperature shocks are exogenous and only affect the outcome variables in (2) through their impact on corn yields and farm cash flow. As discussed below, in support of this assumption, using placebo regressions we do not find any effects of weather shocks on the various outcome variables in non-crisis periods when financing frictions are less likely to bind, despite the fact that weather shocks continue to affect yields.

One potential concern in the interpretation of our results stems from farmers' ability to hedge weather shocks by purchasing crop insurance. However, due to the relatively late development of crop insurance in the United States, hedging is of limited concern in our empirical setting. Indeed, while crop insurance markets have been available since the 1930s, they operated on a limited basis until the 1990s, during which time the U.S. government passed a number of laws that greatly expanded the insurance market (see,. e.g., Cornaggia 2013).[14] Further, the presence of hedging would bias our effects

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[13] We cluster standard errors at the year level in order to account for spatial correlation between counties, since temperature shocks are likely to be correlated across nearby counties. By doing so, we are assuming that all counties in Iowa are correlated, regardless of their distance to one another – a stronger assumption than a typical spatial correlation adjustment of standard errors (e.g. Conley 1999) which assumes that the correlation decays with distance. Our results are also robust to correcting for generalized spatial correlation using the procedure of Driscoll and Kraay (1998).

[14] Federally subsidized crop insurance was introduced by the Federal Crop Insurance Act of 1980. However, this law did not result in significant growth in crop insurance participation, which remained very low throughout the 1980s (Glauber 2013; Hart and Babcock 2000). In the 1990s, laws such as the Federal Crop Insurance Reform Act of 1994 provided for greatly expanded governmental subsidies in support of crop insurance and also implemented mandatory catastrophic coverage in order to protect producers against major losses. As a result of this law, as well as other laws passed in the 1990s, crop insurance coverage rose substantially to more than two thirds of total planted field crop acreage by the end of the decade (see the USDA Risk Management Agency, http://www.rma.usda.gov/aboutrma/what/history.html). Cornaggia (2013) measures the increase in the use of crop insurance showing, for example, a nearly ten-fold increase in the maximum potential insurance liability per farm from the early 1990s to the late 2000s. It should be noted that a key driver in passing the series of crop insurance laws in the 1990s was the 1980s farm debt crisis itself (see, e.g., Stam and Dixon 2004).

downward, as any crop insurance or weather-related governmental transfers to the agricultural sector would make farm net worth less sensitive to the effect of weather shocks.

2.2 Data Sources

We construct a novel dataset of county-level outcome variables in Iowa using a variety of sources. For our temperature data, we collect daily weather station data for Iowa from the National Oceanic and Atmospheric Administration (NOAA) from 1950 to 2010. Using this daily data, we calculate for each weather station the number of days in the corn growing season (from April 1st to September 30th) with an average daily temperature above 83°F.[15] We then construct county-level estimates of this temperature measure for Iowa following the procedure in Deschênes and Greenstone (2012): Using geographical data for each county in Iowa from the U.S. Census Bureau, we construct a county-level estimate of the annual number of hot days (i.e. above 83°F) in the growing season by using a weighted average of all weather station estimates within a 50 kilometer radius of the geographical center of each county. The weights used 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 process yields a total of 6,032 county-year temperature observations for the sample period 1950–2010, and 693 observations for the crisis period 1981–1987.

Our measure of corn yields comes from the USDA's National Agricultural Statistics Service (NASS) yearly crop surveys. The NASS provides yearly county-level data 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 of the

[15] As is common in the literature, in any given year we only use weather stations that have non-missing data for every day in July.

average value per acre of Iowa farmland from 1950 to 2010.[16] Studies have shown that these survey values closely track actual land sales prices (see e.g. Stinn and Duffy 2012; and Kuethe and Ifft 2013).[17]

We use two different data sources to examine the effect of weather-driven shocks on banks. The first source is data on agricultural loan delinquencies from the Federal Reserve's Commercial Bank Data Call Reports. Delinquent loans are defined at the bank level as the outstanding balance of agricultural loans that are 90 days or more past-due and upon which the bank continues to accrue interest (these data are available from 1984 to 2000). For each county in Iowa, we aggregate delinquent balances of all banks headquartered in that county, to obtain a county-level measure of delinquent agricultural loans.[18] In addition, we use data on bank failures for each county taken from the Federal Deposit Insurance Corporation (FDIC). These data run from 1950 to 2010. In order to properly attribute the effects of temperature shocks during the growing season to subsequent bank failures, we mark a bank failure as occurring in year t if it occurred within the period from the end of the growing season in year t (October and onwards) through the growing season of year t+1.

Our final data source is the Quarterly Census of Employment and Wages taken from the Bureau of Labor Statistics. We collect data on county-level employment, average annual wages, and total county-level wages. The data are available for the period 1975–2000. The agricultural crop production sector is defined as SIC code 01. In addition, we use the services sector (SIC division 0I) and manufacturing sector (SIC division 0D). A caveat with our agricultural wage and employment data

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

[17] The micro-level transaction data from Hamilton county used in Section 3.2 are consistent with these studies, showing that the actual transaction prices and the land values from the survey data are very similar. For example, from 1970 to 1987, the mean sales price from the transaction data for Hamilton county was $4,957 compared to a mean land value from the survey of $5,033. Similarly, the median sales price from the transaction data over this period was $4,808, compared to a median land value from the survey of $5,055.

[18] Note that Call Report data do not provide information by borrower location. However, since most banks headquartered in Iowa are relatively small, loans by these banks are generally originated to borrowers located in the vicinity of bank headquarters.

is that the Quarterly Census of Employment and Wages only covers larger farms – it does not cover most agricultural workers in small farms or self-employed agricultural workers.[19]

2.3 The Farm Debt Crisis

The period preceding the 1980s farm debt crisis exhibited sharp increases in debt levels and land values, as common in many financial crises.[20] During the 1970s, increasing commodity prices along with an expansion in demand for U.S. exports of agricultural commodities led to increased farm production and greater investment in farmland. Between 1971 and 1980, agricultural exports roughly doubled, the real price of commodities such as corn increased by over 35 percent, while farmland values rose by 88 percent (see Calomiris, Hubbard, and Stock 1986). During this period of land price appreciation, leverage played an increased role in the financing of agricultural land purchases.[21] For example, whereas in 1950, 42 percent of all agricultural land transactions occurred with no debt financing, by 1978 only 11 percent of transactions occurred without relying on debt capital. The increased reliance on debt, coupled with rising farmland prices, led to a 66 percent increase in aggregate farm debt levels over the period 1971-1980 (Calomiris, Hubbard, and Stock 1986).

The farm debt crisis is generally thought to have been triggered in the early 1980s by the combination of several factors. The first was a tightening of monetary policy undertaken by the Federal Reserve in 1979 under Paul Volcker, which increased interest rates and raised the burden of farmer debt repayment. The interest rate increase also contributed to a strengthening of the U.S. dollar, making U.S. agricultural exports less competitive in the global market. Finally, the U.S. implemented a ban on grain exports to the Soviet Union in 1980, which contributed to a further decline in exports.

[19] In particular, the Quarterly Census of Employment and Wages data do not include farms which consistently employed fewer than 10 individuals in agricultural labor or which paid less than $20,000 in total cash wages to individuals employed in agricultural labor during the current or preceding calendar year.
[20] For a historical survey of the 1980s farm debt crisis, see Harl (1990) and Barnett (2000).
[21] See FDIC Division of Research and Statistics (1997).

As a result of these factors, many farmers who had invested heavily in production over the previous decade, often increasing their leverage in the process, faced a sudden reduction in demand for agricultural commodities coupled with a large increase in the cost of borrowing. The result was a period of severe financial distress and deleveraging in the agricultural sector with significant drops in farm income, sharp declines in farmland values, impaired farm balance sheets, and an erosion in farm credit conditions.

From 1981 to 1987, the average value of farmland dropped by 50 percent across corn-belt states (Barnett 2000). Nationwide, non-performing loans at agricultural banks rose from 2.8 percent of total loans in 1982 to 6.7 percent in 1986, and 100 small agricultural banks failed in 1984 and 1985 alone (see Calomiris, Hubbard, and Stock 1986; and FDIC Division of Research and Statistics 1997). The farming sector saw significant deleveraging with total real agricultural debt declining by 37 percent from 1981 to 1987. In Iowa, real farmland prices dropped by an average of 67 percent across all counties between 1981 and 1987, with 39 commercial bank failures in that period. Furthermore, the majority of bank failures – 34 of the 39 – occurred between 1984 to 1987, considered to be the peak of the crisis.

2.4 Summary Statistics

Table 1 presents summary statistics of the main variables.[22] Panel A provides summary statistics for the debt crisis period defined from 1981 to 1987, while Panel B provides summary statistics for the height of the crisis from 1984 to 1987. For comparison, Panel C provides summary statistics for the non-crisis period.

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[22] In order to mitigate the impact of extreme outliers, we winsorize *Corn Yield* and all other outcome variables (except for indicator variables) at the 0.1 percent level. (To be clear, this winsorization is at the 0.1 percent level – not at the 10 percent level.)

During the crisis years of 1981 to 1987, the average number of days in the growing season with an average temperature exceeding 83°F is 3.25, while the average number of days above 83°F outside of the crisis is 2.51. As would be expected, the average annual number of days above 83°F during the growing season does not differ substantially in the crisis period as compared to the non-crisis period.[23] Figure 1 reports density plots of the distribution of days above 83°F over our entire sample. As can be seen from the figure, roughly 45 percent of the county-year observations have one or fewer days with an average temperature above 83°F, while the density function is monotonically decreasing. As our main specifications include county and year fixed effects, Figure 1 exhibits variation that we do not exploit in our identification strategy. Figure 2, therefore, presents density plots of temperature variation demeaned with year and county fixed effects. The distribution of demeaned days above 83°F appears symmetric around zero, but also exhibits substantial variation. Density plots for individual years (Figure 3) in the crisis and non-crisis period indicate substantial variability across counties for any given year, with some years exhibiting a significantly higher number of days above 83°F.

As can further be seen in Table 1, mean corn yields range from 105.7 to 123.8 bushels per acre. The mean land value during the 1981-1987 period is $2,948 per acre and is $1,978 per acre during the 1984-1987 period (all in real 2010 dollars). Finally, agricultural loan delinquencies are higher during the crisis, as would be expected. Figure 4 depicts the evolution of average corn yield, land value, and agricultural debt across all counties during the sample. Average corn yields increase over the sample period, while land values increase gradually from 1950 to 1970, and then substantially from 1970 to 1980. 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. Finally,

[23] A comparison of means is unable to reject equality.

agricultural debt increases steadily from 1960 to 1980 but drops significantly during the farm debt crisis, as would be expected by a deleveraging process common in financial crises.

A potential concern is that our results are driven by confounding differences between counties that are correlated with the weather shocks. While placebo tests (reported below) establish that our outcome variables are not correlated with weather-driven shocks in the non-crisis period, we further examine a host of other observable county characteristics, comparing county-year observations with below-median number of hot days (as measured by the weather shock variable *Days Above 83*) to county-year observations with above-median number of hot days.[24] Panel D of Table 1 provides the comparison of means. As can be seen, across all of the variables examined, we do not find a statistically significant difference between counties with higher- versus lower-hot days prior to the crisis.

3 Empirical Results

We begin our analysis by confirming that county-level weather variation is indeed related to farm yields in our data.

3.1 Weather Shocks and Crop Yields

As described above, to measure weather shocks we construct a variable, *Days Above 83*, defined at the county-year level, which equals the number of days during the growing season where the average daily temperature within the county was above 83°F. This temperature threshold is taken from Schlenker and Roberts (2009), although our results are robust to alternate definitions of high temperature values.

[24] These variables include total employment rate, aggregate and average wages across all industries, dividend income per capita, county acreage, corn crop acres planted, and total county population.

We confirm in our data the relation between yield and weather shocks found in the agronomics literature by running the following reduced-form specification:

$$\log\left(Y_{i,t}\right) = \beta_0 + \beta_1 (\textit{Days Above 83})_{i,t} + \delta_t + \gamma_i + \varepsilon_{i,t} . \qquad (3)$$

$Y_{i,t}$ is corn yields (bushels of corn produced per acre) in county i in year t, and *Days Above 83* is the weather shock variable capturing hot average-temperature years. Regressions include a vector of year fixed effects (δ_t) and a vector of county fixed effects (γ_i). A potential concern with the regression above is that the error terms may be correlated across nearby geographical regions. In particular, temperature shocks to counties geographically close to one another are likely to be correlated, which will bias the standard errors in a typical OLS regression. To address this, we follow the literature in agronomics (e.g. Deschênes and Greenstone 2007; Schlenker and Roberts 2006, 2009) and calculate standard errors correcting for spatial correlation as in Conley (2008).

Table 2 reports the results of regression (3) over the farm debt crisis sample period of 1981 to 1987. Employing year, but not county, fixed effects, Column 1 shows that high temperature is indeed detrimental to corn yields. Column 2 shows that adding county fixed effects does not substantially change the results. As the coefficient on the weather shock variable, *Days Above 83*, shows, adding an extra day during the growing season with an average temperature above 83°F reduces annual corn yields by 3.3 percent. While seemingly high, this result is consistent with much prior work in the agronomics literature, such as Schlenker and Roberts (2009). Corn is extremely sensitive to high temperature values during the growing season – an established fact that lies at the heart of our identification strategy. It is plausible that the size of the cash flow shock caused by *Days Above 83* will also depend on the number of corn acres in the county. To account for this possibility, we re-run our main regressions weighting by the number of corn acres planted. As can be seen in Table A1 in the Appendix, we find nearly identical results to our main findings.

To give a sense of the dollar magnitude implication of weather shocks on farm profit, it is useful to consider the following back-of-the-envelope calculation of the impact of a 10 percent reduction in yields due to bad weather. This 10 percent reduction in yields is approximately equal to the effect of three additional hot days during the crisis, representing a weather shock smaller in magnitude than the standard deviation of *DaysAbove83* (equal to 4.63). Given that the average yield during the crisis was 123.8 bushels/acre and the (real) price of corn was $4.10/bushel, a 10 percent decline in yields is associated with a drop in sales of $50.76 per acre (in real 2010 dollars). With 122,854 acres of corn grown at the county-level on average, this implies that a 10 percent reduction in yields is associated with an aggregate county revenue drop of $6.24 million. Assuming that costs are unaffected by the bad weather shock (in fact, costs tend to rise following such a shock), and considering a mean profit margin for farmers of 5.3 percent (Hoppe and Banker, 2006), the 10 percent shock in yields ultimately translates to a shift in county-level profits from a positive $3.31 million to a *loss* of $2.94 million.[25]

In Column 3 of Table 2 we report the results for the period of 1984 to 1987 – the peak of the farm debt crisis – and find similar results to Column 2. In Column 4 we estimate the results for the *non-crisis* period. The effect of weather on yields is biological and hence, as expected, the estimated coefficient on the weather shock variable during the non-crisis period (Colum 4) is similar to those during the crisis period (Columns 1-3).

We note here that an additional channel through which financial constraints can amplify the effect of weather shocks stems from their impact on the ability of farms to *adapt* to detrimental shocks. In particular, farmers may respond to adverse weather shocks with various strategies meant to mitigate the effect of hot weather on crop yields – extra fertilizer, more watering, tillage, seed varieties, etc.

[25] To see this, note that with a 5.3% profit margin, profits are expected to be $3.31 million (= $4.1 × 123.8 × 122,854 × 0.053) prior to the 10 percent shock to yields.

(Reilly, 1999). Such strategies naturally require additional financing. However, when external financing is costly, as during a debt crisis, farm adaptation may thereby be constrained, and a given external shock will thus have a larger impact on farm yields and income.[26] Some suggestive evidence for this additional channel may be seen in the fact that the impact of weather shocks on yields is somewhat larger during the crisis years, when the crisis is defined over the period 1981-1987.

3.2 Cash Flow Shocks and Asset Prices

Having confirmed the effect of temperature on yields, we analyze how temperature shocks, and the variation they induce in farm cash flows, affect local land prices. Following cash-in-the-market pricing theories (Shleifer and Vishny 1992; Allen and Gale 1994; and Kiyotaki and Moore 1997), we hypothesize that during debt crises, when financial frictions and the cost of external finance are high, counties that receive negative cash flow shocks stemming from weather variation will exhibit lower agricultural land prices: negative weather shocks reduce the net worth of local buyers – i.e. nearby farmers – who will thus have less funds to purchase land.

As in all models of cash-in-the-market pricing, an implicit assumption required for land prices to be affected by local liquidity conditions is that the market for land is at least partially segmented, in that capital cannot flow seamlessly from afar (see, e.g., Shleifer and Vishny 1992; Allen and Gale 1994, 1998; Duffie 2010). This assumption is likely satisfied in the market for agricultural land, which is generally thought to be highly localized. However, to confirm this assumption, we hand-collect a micro-level dataset on land transactions within one county in Iowa – Hamilton county – between the years 1970 and 1988.[27] For each of the 1,971 sales of agricultural land in Hamilton county, we mark

[26] More generally, a model along the lines of Bernanke and Gertler (1989) which adds the ability of firms to ***respond and mitigate*** negative shocks using increased spending – for example, by raising advertising expenditures to boost sales – implies an additional financial accelerator channel; In this channel, increased costs of external finance will amplify the effect of external shocks by reducing firms' adaptation ability.
[27] The data are hand-collected from the Hamilton county courthouse where they are located in non-electronic form.

the county of the buyer and calculate the monthly fraction of out-of-county buyers.[28] As can be seen in Figure 5, the data confirm that agricultural land sales are highly localized: only 9.4 percent of transactions occur with an out-of-county buyer. Interestingly, the fraction of out of county buyers increases substantially during the financial crisis, reaching 25 percent in 1985. This spike in out-of-county purchases is very much consistent with, and in fact would be predicted by, the existence of fire sales, in which capital from afar flows into the market to buy liquidated assets.

Having confirmed that agricultural land markets are localized, we examine the effect of exogenous county-level weather-induced cash flow shocks on the price of land during the crisis. Table 3 reruns the reduced form specification in regression (3) but employs log(*Land Value*), the average county-level price per acre of farmland (in 2010 dollars), as the dependent variable. Consistent with the prediction of cash-in-the-market pricing, we find that counties that received a positive cash flow injection – driven by relatively good weather – exhibit higher land values than counties that receive a negative cash flow shock – driven by a few additional days of high temperature weather during the growing season. Focusing on Column 2, which includes county fixed effects, an additional day during the growing season with an average temperature greater than 83°F reduces average price per acre by 0.4 percent. In Column 3, which reports the results for the period during the peak of the farm debt crisis, 1984-1987, the estimated magnitudes are even larger: during the growing season, an additional day with average temperature exceeding 83°F reduces land values by 0.8 percent. To our knowledge, this is the first study that provides causal evidence of cash-in-the-market pricing.

The results in Table 3 regarding the relation between weather shocks and land prices focuses on the farm debt crisis period. At the center of the theoretical argument behind this result is the assumption that financial frictions prevent firms from raising external financing to smooth shocks or

[28] An out-of-county buyer is defined as a buyer whose address is located in a different county from Hamilton. We are able to observe the buyer's address through courthouse records.

make it prohibitively costly for them to do so. According to this argument, we thus expect that *outside* of the crisis, the effect of weather shocks on land prices is greatly diminished (or non-existent), even while these shocks continue to affect yields and hence cash flows. Column 4 conducts this test by considering the impact of exogenous weather shocks outside of the 1980s farm debt crisis. As can be seen, in contrast to the results in Columns 1-3 of Table 3, weather variation outside of the crisis years has no statistically significant relationship with land prices, consistent with an increased ability of firms to smooth cash flow shocks. Thus, even though negative weather shocks continue to detrimentally affect yields outside of the crisis (see Table 2, Column 4), they have no effect on land values outside the crisis.[29]

Table 3 provides a reduced form estimation of the relation between weather shocks and land values. To estimate the elasticity of land values to exogenous variation in yields during the debt crisis, we employ the following instrumental variable approach. The first stage instruments for yields using exogenous weather shocks, as in regression (1) above, while the second stage relates county average land values to the predicted yields taken from the first stage. Specifically, we run:

$$\log\left(Land\ Value_{i,t}\right) = \beta_0 + \log\left(\widehat{Yield_{i,t}}\right) + \delta_t + \gamma_i + \varepsilon_{i,t}\ , \tag{4}$$

where $\log\left(\widehat{Yield_{i,t}}\right)$ is instrumented log corn yield in county i in year t estimated via (1), and $Land\ Value_{i,t}$ is the average land value (in 2010 dollars per acre) of county i in year t. As in all specifications, δ_t, represents a vector of year fixed effects, and γ_i represents a vector of county fixed effects.

The results are shown in Table 4. Column 1 of the table provides the first-stage estimation. Column 2 of the table exhibits the results of the second stage, finding an elasticity of land values to

[29] One concern regarding the relation between land values and weather-driven cash flow shocks is that potential buyers might mistakenly believe that temporary weather shocks are indicative of longer-term shifts in weather activity. This, for example, could arise due to a behavioral bias by which, following a negative weather shock, potential land buyers overestimate the conditional probability of future negative weather shocks. However, this expectation-driven explanation is not consistent with the fact that land values exhibit no relation with weather shocks outside of the crisis.

yields of 0.12 – a 10 percent exogenous increase in county yields is thus associated with a 1.2 percent increase in land values during the debt crisis. Columns 3 and 4 conduct the instrumental variable strategy starting from 1984 – the height of the crisis years – and up to its end in 1987. Consistent with higher financial constraints during the height of the crisis, the second stage elasticity of land prices to yields is 0.34, or roughly three times larger than the effect during the full crisis period.

It is instructive to consider the magnitude of these results in light of the impact of weather shocks on aggregate county revenue. As noted in Section 3.1, a 10 percent change in yields during the crisis is associated with a change in aggregate county farm revenue of $6.24 million. Given the elasticity estimates in Table 4, a 10 percent drop in yields causes a 1.2 percent decline in land values, which given the average county land value per acre of $2,948, implies an aggregate decline in county land values of $4.35 million. Thus, a $6.24 million shift in county level revenue is associated with a $4.35 million shift in aggregate county land values. Consistent with cash-in-the-market pricing, the results thus imply an economically significant dollar-sensitivity of land values to cash flow shocks of 0.70 (=4.35/6.24).[30]

3.3 Cash Flow Shocks and the Financial Sector: Delinquencies and Bank Failures

Having shown how weather shocks affect yields and land prices, in this section we analyze how temporary shocks to cash flow during the debt crisis propagated into the financial sector. In the presence of financial frictions, temporary – i.e. short lived – weather shocks during a crisis affect farmers' repayment ability, in turn leading to defaults. Thus, farmer inability to smooth temporary

[30] We note that in a cash-in-the-market pricing setting, the exact magnitude of the relation between cash flow changes and land values is complex, as it is determined by two important factors – the price elasticity of the supply of land being sold on the market and the fraction of cash holdings devoted to land purchases. The sensitivity of aggregate county land values to a dollar change in county farm income can be greater or smaller than one, depending on these parameters. In our setting, although we can estimate the magnitude of the change in county revenue and profits, we do not know the magnitude of these two additional parameters – the elasticity of the supply of land sold and the fraction of cash devoted to land purchases – and therefore it is difficult to pin down the predicted sensitivity of county land values to changes in aggregate county income.

weather shocks in a crisis is predicted to create long lasting effects in the financial sector in the form of borrower defaults and bank failures. [31]

To analyze the propagation of shocks from the real sector to the financial sector during a debt crisis, we first verify that negative weather-driven cash flow shocks do indeed translate into higher delinquencies on agricultural loans during the crisis. For each county-year we calculate the aggregate outstanding balance of agricultural loans that are 90 days or more past due. Data on agricultural loan delinquencies are taken from the Federal Reserve Call Reports. As in the prior section, we employ an instrumental variable approach that runs a first-stage regression in which county average corn yields are instrumented with *Days Above 83*, the weather shock variable. The second stage then relates county-level aggregate balance of delinquent loans to county average yields.[32] Specifically we run:

$$\log\left(Ag\ Delinquencies_{i,t}\right) = \beta_0 + \log\left(\widehat{Yield_{i,t}}\right) + \delta_t + \gamma_i + \varepsilon_{i,t}\ , \tag{5}$$

where, as in prior regressions, $\log\left(\widehat{Yield_{i,t}}\right)$ is instrumented log corn yield in county i in year t estimated via (1), δ_t, represents a vector of year fixed effects, γ_i represents a vector of county fixed effects, and *Ag Delinquencies* is the total outstanding balance of delinquent agricultural loans.[33]

Panel A of Table 5 presents the results. As can be seen in Column 1 of the table, delinquency levels vary negatively with yields. The results imply an elasticity of 3 between county aggregate delinquent loans and county average yields: during the crisis, counties which experience a 10 percent weather-driven exogenous increase in yields (as compared to their mean) exhibit a 30 percent decrease in aggregate delinquency levels.[34] As would be predicted, exogenous positive cash injections translated

[31] For the importance of bank-level financial constraints, see, e.g., Bernanke and Blinder (1988); Kashyap and Stein (2000); and Bernanke and Gertler (1995).

[32] See Column 3 of Table 2 for the first stage results.

[33] We add one to the outstanding balance of loans before taking logs, in order to accommodate zero values.

[34] This is in line with the impact of a 10 percent shock to yields on farm revenue. For example, as previously noted, a 10 percent reduction in yields due to weather implies that farmers experience an aggregate county revenue loss of $6.24 million leading to negative county profits of $2.93 million. The coefficient estimate and sample mean suggest that this same 10 percent shock would lead to an increase of roughly $230,000 in aggregate county agricultural loan delinquencies as a result of farmers experiencing profit losses.

into reduced delinquencies among borrowers.

Loan delinquencies represent, of course, shocks to bank balance sheets. As a next step, we examine to what extent exogenous variation in loan delinquencies transmit into the local financial sector in the form of subsequent county bank failures. We employ our standard instrumental variable approach, first instrumenting county average yields with the weather shocks, and then relating the instrumented yields to bank failure rates at the county-level. Specifically, we run the following instrumental variable linear probability model:

$$Bank\ Failure_{i,t} = \beta_0 + \log\left(\widehat{Yield_{i,t}}\right) + \delta_t + \gamma_i + \varepsilon_{i,t}\ , \tag{6}$$

where *Bank Failure*$_{i,t}$ takes on the value of one if there was a bank failure in county *i* in the period following the growing season in year *t* up to the end of the growing season in the following year, and zero otherwise. As usual, $\log\left(\widehat{Yield_{i,t}}\right)$ is instrumented log corn yield in county *i* in year *t* estimated via (1), δ_t is a vector of year fixed effects, and γ_i is a vector of county fixed effects.

Column 2 of Table 5A presents the results. As the table shows, a 10 percent decrease in yields leads to an approximately 3.2 percentage point increase in the probability of bank failure. The effect is economically sizeable, as 28 percent of the county-year observations during the period of 1984 to 1987 exhibit a bank failure.[35] Consistent with the hypothesis, temporary cash flow variation driven by exogenous weather shocks did indeed lead to spillovers into the financial sector in the form of bank failures.

Column 3 of the table repeats the analysis, but allows a lag in the time to bank failure. Specifically, we define an indicator variable, *Bank Failure Crisis*, that takes on the value of one if there was a bank failure from the given year until the end of the crisis (i.e. to 1987), and zero otherwise. As

[35] As discussed above, a 10 percent weather-driven decline in yields reduces county-level farm revenue by \$6.24 million (in real, 2010 dollars), shifting aggregate county profits from \$3.31 million to a loss of \$2.93 million. Given the depleted level of bank capital during the crisis – the 25th percentile of (real) bank capital during the debt crisis was only \$2.8 million, and the 10th percentile was only \$1.9 million – the increase in bank failure rates seems justifiable.

can be seen, the effect of predicted yields on bank failures rises when a time lag to failure is accounted for, with a coefficient in the level-log specification that is approximately -0.4.

As a placebo test, Panel B of Table 5 examines the effect of temporary cash flow shocks outside of the debt crisis. Lower financial frictions and stronger balance sheets during this period would predict muted effects. This is indeed what the results indicate. As can be seen in Column 1 and Column 2 of Table 5B, cash flow shocks outside of the crisis are not related to delinquencies or bank failure rates in a statistically significant manner.

3.4 Cash Flow Shocks and Labor Markets: Employment and Wages

We continue by analyzing the effect of weather-driven cash flow shocks during the crisis on local employment and wages, focusing first on the agricultural sector itself. Panel A of Table 6 focuses on the debt crisis years, examining the relation between weather-driven variation in yields and labor markets outcomes within the agricultural sector. We analyze county average pay and county employment levels, as obtained from the Quarterly Census of Employment and Wages. All regressions employ the instrumental variable approach, whereby county average yields are instrumented first with the weather shock variable, and then predicted yields are related to either wages or employment. Specifically, we run:

$$Y_{i,t} = \beta_0 + \log\left(\widehat{Yield_{i,t}}\right) + \delta_t + \gamma_i + \varepsilon_{i,t} \, , \tag{7}$$

where Y_{it} is a county-level labor-market outcome, and $\log\left(\widehat{Yield_{i,t}}\right)$ is instrumented log corn yield in county i in year t estimated via regression (1). We examine three labor-market outcomes: total county-level wages in the agricultural crop sector (*Ag Total Wages*), average county-level annual wage for an employee in agricultural crop production (*Ag Avg Wages*), and total county-level employment in agricultural crop production (*Ag Employment*).

Column 1 of Table 6A exhibits results using total county-level employment as the dependent variable.[36] As can be seen, there is a positive relation between yields and total county employment. Estimating the economic magnitude of the effect, a one percent drop in yields reduces agricultural employment by 4.1 percent of the sample mean. Thus, during the crisis, farms in counties that received a positive cash flow injection (driven by relatively good weather) reduce their total agriculture employment by less than those that received a negative cash flow shock. Consistent with increased financial frictions during the crisis, temporary shocks to firm balance sheets affect employment rates. When financial constraints bind and external capital is costly, labor demand can be influenced by firm net worth.

Continuing with labor market outcomes, Column 2 of Table 6A replaces employment with average county wages per employee as the dependent variable. As can be seen, predicted crop yields are positively related to average wages per employee. Counties that experienced a negative weather-induced cash flow shock exhibit a relative decline in average wages per employee, consistent with a drop in labor demand stemming from reduced ability to finance employee wages out of internal capital. The elasticity of yields to average county pay is 2.9: a one percent reduction in yields is associated with approximately a three percent relative reduction in average wage per employee. Column 3 analyzes total county wages, which combines variation in total county employment as well as variation in county average wage per employee. Unsurprisingly, given the results in the prior two columns, we find that weather driven cash flow injections are positively related to total county wages.

Panel B of Table 6 repeats the analysis but focuses on the period outside of the farm debt crisis. Outside of financial crises, firms' ability to smooth temporary cash flow shocks is greatly enhanced, and so we expect the relation between employment and predicted yields to be dampened.

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[36] Note that the data from QCEW does not include information for small farms. As small firms are generally thought to be more financially constrained (see, e.g., Gertler and Gilchrist 1994; Beck, Demirgü-Kunt, and Maksimovic 2005; and Hadlock and Pierce 2010), this suggests that the results here underestimate the true relation between yields and labor market outcomes. Because some counties have few large farms, we run employment in levels; however, running employment in logs gives a significant coefficient of 1.22 with a standard error of 0.52.

Consistent with this, the results show that outside of the debt crisis, county level employment, average wage per employee, and total wages are unrelated to exogenous weather-driven variation in yields. While the strength of a firm's balance sheet, and variation in it, plays a role in determining labor market outcomes during periods of high financial constraints, they play no role outside of the crisis. The results thus suggest that cash injections into the real sector affect labor market outcomes during a debt crisis, but not outside of it.

Table 7 continues by analyzing how cash flow shocks spill over into other labor markets during the debt crisis. Specifically, we use the instrumental variable strategy from above to relate variation in predicted yields to local level employment and wages in the *service* sector – a natural sector where employees dislocated from farming might seek employment.[37] Column 1 of Table 7A shows that total county-level employment in the service sector is *negatively* related to weather-driven cash flow shocks in the agricultural sector: when a county is hit with a negative cash flow shock in the agricultural sector, the data show that agricultural employment declines while employment in services rises (compared to the mean county level).[38] Following a negative cash flow shock, workers thus appear to shift from the adversely affected agricultural sector towards other industries. The results in Column 1 of the table show that a one percent reduction in county predicted yields is associated with a 0.34 percent increase in county-level service sector employment relative to the sample mean.

Still focusing on the debt crisis period, Column 2 of Table 7 examines how average wages in the service sector relate to cash flow shocks in the agricultural sector. Consistent with an outward shift in the supply of workers in services, the coefficient on predicted yields shows that counties that experienced an exogenous negative weather-driven cash flow shock in agriculture exhibit a relative decline in wages in the service sector. As workers shift from agriculture to services, labor supply rises

[37] We note that we find no statistically significant adjustments in manufacturing employment in response to weather-driven dislocation in the agricultural sector. Data are taken from QCEW as discussed earlier.
[38] Running employment in logs gives a negative, but insignificant, coefficient of -0.08.

and, correspondingly, wages in the sector decline. The elasticity of average county wages in the service sector to county yields is 0.075 – i.e., a ten percent decline in agricultural yields translates into a 0.75 percent drop in service sector wage.

Column 3 of the table examines total county wages in the service sector and finds that these are unrelated in a statistically significant manner to yields. This is not altogether surprising, as the effect on wages and employment run in opposite directions following a negative shock to yields: while average wages in the service sector falls, county employment in the sector rises.

Taken together, the results in Panel A of Table 7 paint a picture by which, during a debt crisis, firms' inability to smooth shocks in one sector create externalities in other sectors within the labor market. Workers shift away from firms hit by temporary cash flow shocks, increasing the supply of labor in other sectors. The result is higher employment and lower wages in sectors unrelated to the original cash flow shock.

For completeness, Panel B of Table 7 conducts a placebo test and reruns the specifications of Panel A focusing on the period outside of the crisis. As was shown in Panel B of Table 6, outside of the crisis weather shocks do not affect agricultural employment. Because the agriculture sector is able to smooth cash flow shocks, we expect to find no effect on labor outcomes in the services sector outside of the crisis. This is indeed what the results show. Using the instrumental variable specification outside of the crisis, none of the service sector labor market outcomes are related in a statistically significant manner to (predicted) county level yields.

We next test a second channel – related to shifts in demand – through which cash flow shocks during a financial crisis can spill over into other sectors. The results in Table 6 show how sectoral cash flow shocks during a financial crisis translate into labor market dislocation within the agriculture sector, as firms find it difficult to utilize capital markets to smooth temporary funding shortages. Accordingly, we test the following demand channel for inter-sector spillovers during financial crises:

once a given sector is hit by a cash flow shock, firms in the sector cut employment, causing dislocated employees to reduce overall consumption. The shock to the first sector thus propagates into other sectors, which, faced with a reduction in demand, cut employment in their respective sectors.[39]

To test this mechanism, we run similar regressions to those in Table 7 relating employment and wages in the service sector to weather-induced cash flow shocks in agriculture, but interact the weather-driven cash flow shocks with a measure of the importance of agriculture within each county. Weather shocks are measured, as usual, using the number of growing season days with average temperature above 83°F, while the importance of agriculture within each county is measured by the ratio of farm crop income to total income within each county.[40] We predict that in counties with a dominant agriculture sector, negative (weather-driven) cash flow shocks will lead to greater declines in overall demand, which will tend to reduce employment in the service sector. This demand-driven effect goes in the opposite direction to the reallocation effect analyzed above whereby workers from agriculture move into other sectors following a cash flow shock in the agriculture sector.

Column 1 of Table 8A presents the results of the interaction specification, analyzing the effect of weather-driven cash flow shocks on service sector employment. As can be seen, the coefficient on the non-interacted weather shock is positive, but the coefficient on the interaction term between the weather shock and the county-level agricultural importance is negative. Thus, as in Table 7 above, in counties where farming plays a relatively small role, negative cash flow shocks in agriculture tends to increase employment in services – a reallocation channel. However, if agriculture plays a sufficiently large role in a county, cash flow shocks in the agriculture sector *reduce* employment in services. At the 25th percentile of agricultural importance within the county (captured by the ratio of farm crop income

[39] Examining a demand channel, Mian et al. (2013) analyze how local-level shocks to household balance sheets driven by the 2006-2009 collapse in housing prices affect household consumption, while Mian and Sufi (2014) analyze how this household balance sheet shock reduced employment during the 2008-2009 crisis.

[40] Specifically, we construct this cross-sectional county-level measure by calculating for each county the mean ratio of farm crop income to total county income over the period 1969-1980.

to total income), an additional hot day with temperature above 83°F increases service sector employment by 1.3 percent of the sample mean, but in contrast, at the 75th percentile of agricultural importance such a weather shock *reduces* service sector employment by 0.8 percent. Thus, during a debt-crisis, aggregate county-level cash flow shocks in one sector impose employment externalities on other sectors operating within the same geography. The sign of these externalities depends on the relative importance within the economy of the sector receiving the shock.

Column 2 of Table 8A repeats the analysis but analyzes the impact on service sector wages (rather than employment). We predict that detrimental weather-driven cash flow shocks reduce wages and that this effect will be greater when agriculture plays a larger role within a county. However, as can be seen in the table, while the non-interacted coefficient on weather shocks does indeed predict a reduction in wages following a negative cash flow shock, the coefficient on the interaction term with the fraction of county-level farm income is not statistically significant.

Panel B of Table 8 repeats the interaction specification in Panel A of the table, but uses the instrumental variable strategy relating labor market outcome variables to predicted log yields (as in Table 7 above). To this end, we separate the sample into two based on median county-level farm importance, and rerun instrumental variable specifications for below median and above median farm importance counties.[41] The results are consistent with those in Table 7. Employment in services is positively related to predicted yields in counties with above-median farming importance but is negatively related to predicted yields in counties with below-median farming importance. Negative weather-driven cash flow shocks thus decrease employment in services amongst counties where farming plays a large role – consistent with a demand-channel effect – but increases employment in counties where farming plays a relatively smaller role – consistent with a reallocation effect. Further,

[41] The median ratio of farm income to total county income is 0.226.

as can be seen from Columns 2 and 4 of Table 8B, wages are positively related to predicted yields, although the effect is not statistically significant in above-median farming importance counties.

We note that the reason that the point-estimate on services-employment in the pooled sample in Table 7A does not lie in between the point-estimates on services-employment in the two subsamples in Table 8B is that the pooled regression allows for only one set of fixed effects, while the subsample regressions allow for two different sets of fixed effects (i.e., each subsample has its own set of fixed effects). Indeed, re-running the pooled IV regression in Table 7 with interaction terms between the year fixed effects and an indicator variable based off of median fraction of agricultural income – i.e. the same criteria used to create the sample split – results in a coefficient on predicted yields which lies in between the analogous coefficients in the two subsamples, as would be expected. These results are provided in Table A2 in the Appendix.

3.5 Banking Market Frictions and the Heterogeneous Effect of Cash Flow Shocks

In this section we test whether increased financing frictions at the local level affect the impact of weather-driven cash flow shocks on the real and financial outcomes described above. To this end, we exploit cross-sectional variation in local banking market characteristics and the degree of financing frictions therein. We hypothesize that in markets with greater bank financing frictions, weather-driven shocks will have a larger effect on the variables of interest, as banks, and hence the farms which rely on them, are less able to smooth the impact of negative shocks.[42]

In order to test this hypothesis, we proxy for local bank financing frictions by calculating the aggregate loan-to-deposit ratio for banks in each county prior to the crisis (following, for example, Acharya and Mora, 2015).[43] We then rerun the specifications relating weather shocks to the real and

[42] We thank an anonymous referee for suggesting the empirical tests in this section.
[43] The loan-to-deposit ratio is commonly used to assess banks' liquidity, and thus their ability to cover funding requirements. A county is defined as high (low) Loan-to-Deposit if its mean ratio of aggregate loans to deposits for banks

financial outcomes described above, splitting the sample between counties which had high Loan-to-Deposit ratios and counties with low Loan-to-Deposit ratios. The results are presented in Table 9.

As can be seen in the table, the results show that for all dependent variables but one – services employment – the effect of (instrumented) yields on the dependent variable of interest is indeed greater in counties with greater bank financing frictions. Thus, for example, we find that the relation between the elasticity of land values to instrumented yields is approximately 40 percent greater in high Loan-to-Deposit counties as compared to low Loan-to-Deposit counties. Similarly, the impact of instrumented yields on agricultural employment is more than three times larger in counties with high Loan-to-Deposit ratios as compared to in low Loan-to-Deposit ratios (with the effect in the latter counties not statistically different from zero.)

As mentioned above, employment in the services sector is the only variable that does not exhibit a stronger sensitivity to weather-driven shocks in counties with high bank financing frictions. Indeed, the results indicate that the impact of weather shocks on employment in the services sector are smaller in counties with larger bank financing frictions (i.e. high Loan-to-Deposit ratios). We note, though, that the predicted effect of bank financing frictions on the sensitivity of services employment to weather shocks is ambiguous: on the one hand, employment in agriculture is predicted to drop more, but on the other hand, when financing frictions are large, the ability of firms in the services sector to *absorb* the dislocated employees could be impaired, as hiring employees could strain finances (for financial friction effects on employment see, e.g., Chodorow-Reich, 2013, and Falato and Liang, 2016). Our results are consistent with the second effect dominating the first.

3.6 Cash Flow Shocks and Income Per Capita: The Income Multiplier During the 1980s Farm

from 1975 to 1980 is above (below) the sample median. County loan-to-deposit ratios are calculated using Call Report data.

Debt Crisis

The results of the prior sections show how exogenous county-level cash flow shocks during the debt crisis had a sizeable effect on a host of real outcomes across a number of markets. These include the market for land, labor markets, and the local banking sector. A natural question to ask, then, is whether and to what extent cash flow shocks ultimately affect county-level income during the debt crisis. To investigate this question, we use our standard instrumental variable approach regressing the log of county income per capita on the log of county-level yields, with yields instrumented by the exogenous weather shock variable *Days Above 83*.

The results are presented in Table 10. As can be seen, during the farm debt crisis, instrumented yields are positively related to income per capita, with an elasticity of 0.138. In contrast, the point coefficient on predicted yields outside of the farm debt crisis period is approximately one third as much and not statistically significant.

It is instructive to use the results in Table 10 to conduct a back-of-the-envelope calculation of the local-level cash flow to income multiplier – i.e., the increase in county-level income associated with an exogenous dollar injection of cash flow. Based on the elasticity of 0.138 in Table 10, a 10 percent weather-driven drop in yields during the crisis is associated with a 1.38 percent drop in county income per capita. This 1.38 percent drop is equivalent to a per-capita reduction of \$356.8 from the average county-level income-per-capita during the crisis (\$25,855 in 2010 real dollars). Since the 10 percent drop in yields is equivalent to a reduction of \$219.55 in county per capita corn sales, our results indicate that during the debt crisis, the multiplier between the exogenous county level cash flow shock and county-level income is \$356.80/\$219.55 = 1.63.[44] Based on these estimates, cash flow injections had

[44] As discussed in Section 3.1, a 10 percent drop in yields is associated with a \$50.76 drop in sales per acre, which given the average acreage of grown corn per county of 122,854 and the average county population of 28,402, implies a \$219.55 (= \$50.76 × 122,854 / 28,402) drop in county per capita sales.

a significant impact on local economic income during the crisis.[45]

Our multiplier estimate of 1.63 fits quite nicely with evidence found on local-level fiscal multipliers. For example, exploiting geographic variation in military procurement spending, Nakamura and Steinsson (2014) estimate a fiscal multiplier of expenditures on income of approximately 1.5. Similarly, exploiting variation in population-count methods in non-census years and their impact on government expenditures, Serrato and Wingender (2016) estimate an income multiplier to local government expenditures of between 1.7 and 2.[46]

As a consistency check, the county-level income-to-cash-flow shock multiplier can also be calculated employing the reduced form specification relating yields to the number of high temperature days during the growing season. As can be seen in Column 3 of Table 10, an additional growing season day with temperature above 83°F leads to a 0.3 percent reduction in income per capita, or equivalently, a reduction of $77.57 as compared to the mean income per capita of $25,855 during the crisis. From Table 2, an additional growing season day with temperature above 83ºF leads to a 2.2 percent drop in corn yields during the crisis, which in turn is equivalent to a $48.30 (in 2010 real dollars) drop in county per capita sales.[47] The multiplier between the exogenous cash flow shock and county-level income is thus $77.57/$48.30 = 1.61, which is similar to the 1.63 estimate obtained above.

As a final test, we examine whether, similar to the results in Table 8, the effect of weather shocks on county income is stronger in counties where farming plays a larger role. To this end, we use specifications analogous to those in Table 8 to examine how the relation between county income and weather shocks during the crisis vary by the fraction of county income stemming from agriculture.

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45 As Table 10 shows, outside of the debt crisis, the point estimate of the income-per-capita to yield elasticity is 0.036 with a 95 percent confidence interval of -0.024 to 0.096.

46 For a survey of local-level fiscal multipliers, see Chodorow-Reich, 2019.

47 With an average real price of corn of $4.10 per bushel and an average yield of 123.8 bushels per acre during the crisis, a 2.2 percent drop in corn yields leads to a drop of $4.1 × 123.8 × 0.022 = $11.17 in sales per acre. Given an average acreage of corn grown of 122,854 acres and an average population of 28,402, this gives a drop of $11.17 × 122,854 / 28,402 = $48.30.

The results are presented in Table 11. As predicted, we find increased sensitivity of county income to weather shocks in counties where farming plays a larger role.

4 Conclusion

In this paper, we examine the general equilibrium effects of cash flow injections during a financial crisis. Analyzing the 1980s farm debt crisis, our empirical strategy exploits random weather shocks as a source of exogenous cash flow variation. Our analysis tracks the effect of weather induced cash flow shocks during the crisis on a host of outcomes in the real and financial sector. We find that exogenous cash flow shocks during the crisis have significant effects on land values, loan delinquency and bank failure rates, as well as on employment and wages.

Consistent with cash-in-the-market pricing, during the debt crisis, farms in counties that received a positive cash flow injection – driven by relatively good weather – exhibit higher land values than those that received a negative cash flow shock. Placebo regressions show that the cash-in-the-market pricing effect does not arise outside of the debt crisis when financial frictions are expected to be lower.

Examining the financial sector, we show that exogenous shocks to the real sector propagate into the financial sector during the debt crisis: counties that receive negative cash flow shocks exhibit higher delinquency rates on loans as well as more bank failures. Consistent with financial constraints at the *bank* level, banks thus appear unable to smooth temporary shocks to their balance sheets during the debt crisis.

We also find that exogenous shocks to cash flow have important general equilibrium labor market effects. First, we find that negative shocks to the agricultural sector during the farm debt crisis reduce both employment and wages in that sector. In addition, we find that there are spillover effects into other sectors. In particular, in counties that experience negative shocks during the crisis, employment in the *services* sector increases due to workers being displaced from farming, while the average wage of employees in services drops, consistent with an increase in labor supply. Overall, we find evidence that temporary shocks that affect balance sheets of firms in the agricultural sector during a crisis create externalities for other sectors.

Our results highlight the potential importance of cash injections to firms during a financial crisis when balance sheets are impaired and financial frictions are high. The results also underscore how cash injections in one sector can spill over into other sectors of the economy, both real and financial. Income multipliers during financial crises are shown to be high. Importantly, the economic impact of interventions meant to strengthen real sector balance sheets is state dependent and countercyclical, consistent with financial accelerator models.

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Table 1: Summary Statistics

This table contains summary statistics for all variables. Panel A provides summary statistics for the crisis period defined from 1981 to 1987, Panel B provides summary statistics for the crisis period defined from 1984 to 1987, and Panel C provides summary statistics for the non-crisis period. Panel D provides tests of the differences between various observable variables in the pre-crisis period (before 1981), for counties that are below-median and above-median in terms of days above 83 degrees. All variables are at the county-year level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. *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. *Ag Delinquencies* is the total outstanding balance of agricultural loans that are 90 days or more past-due and upon which the bank continues to accrue interest, in thousands of dollars. *Total Employment Rate* is total county employment scaled by population. *Total Wages* is total (aggregated) county wages across all industries. *Avg Wage* is the average annual wage across all workers in a county. *Dividends per Capita* is the total amount of dividends received in the county per capita. *County Acreage* is the total size of the county in terms of number of acres of land. *Corn Acres Planted* is the number of acres of corn planted in the county. *Population* is the total population of the county. All variables except for *Days Above 83* are winsorized at the 0.1 percent level. Statistics for the non-crisis period in Panel C are presented from 1950-1980 and from 1988-2010, except for *Income* (which is from 1959, 1969-1980, and 1988-2010) and *Ag Delinquencies* (which is from 1988-2000). All dollar amounts are scaled by the consumer price index (CPI), and are in real 2010 dollars. In Panel D, the Difference column runs a t-test of the mean difference between the two groups; *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

***Panel A: Crisis Years*, 1981–1987**

Variable	# Obs	Mean	Std. Dev.	p25	Median	p75
Days Above 83	693	3.25	4.63	0.50	1.62	3.73
Corn Yield	693	116.84	22.03	108.70	121.50	131.60
Land Value	693	2,947.58	1,511.36	1,759.38	2,447.81	4,055.71
Income	693	24,827.96	2,720.39	23,093.07	25,054.18	26,675.79

***Panel B: Crisis Years*, 1984–1987**

Variable	# Obs	Mean	Std. Dev.	p25	Median	p75
Days Above 83	396	2.38	3.07	0.29	1.22	3.05
Corn Yield	396	123.83	15.21	115.15	125.75	134.30
Land Value	396	1,978.40	750.86	1,488.39	1,868.92	2,299.06
Income	396	25,855.09	2,379.82	24,558.87	25,825.22	27,477.96
Ag Delinquencies	396	710.61	684.66	185.47	526.12	1,084.87

Panel C: Non-Crisis Years

Variable	# Obs	Mean	Std. Dev.	p25	Median	p75
Days Above 83	5,339	2.51	3.64	0.05	1.07	3.22
Corn Yield	5,346	105.67	41.47	71.10	100.70	139.10
Land Value	5,346	2,753.69	1,359.75	1,893.49	2,424.75	3,127.98
Income	3,465	27,935.32	6,723.88	23,609.35	27,301.22	32,272.76
Ag Delinquencies	1,279	164.90	276.59	1.26	54.04	214.88

Panel D: Pre-crisis Observable Differences between Counties

Variable	Below-median Hot Days	Above-Median Hot Days	Difference
Total Employment Rate	0.269	0.258	0.011
log(*Total Wages)*	17.643	17.619	0.025
log(*Avg Wage*)	9.117	9.120	-0.003
log(*Dividends per Capita*)	8.403	8.415	-0.012
County Acreage	361,429.2	362,607.5	-1,178.28
Corn Acres Planted	116,619.8	116,432.7	187.114
log(*Population)*	9.876	9.924	-0.048

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. *Corn Yield* is defined as bushels of corn produced per acre of harvested land, and is winsorized at the 0.1 percent level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley 2008), as indicated. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). The crisis period is defined from 1981-1987 in columns 1 and 2, and from 1984-1987 in column 3; the non-crisis period runs from 1950-1980 and 1988-2010; the full sample runs from 1950 to 2010.

Dependent Variable: log(*Corn Yield*)

	(1)	(2)	(3)	(4)
Time Period:	Crisis, 1981-1987		Crisis, 1984-1987	Non-crisis
Days Above 83	-0.034***	-0.033***	-0.022***	-0.026***
	(0.008)	(0.008)	(0.004)	(0.003)
Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes
Standard Errors	Spatial	Spatial	Spatial	Spatial
Observations	693	693	396	5,339
R^2	0.66	0.80	0.75	0.93

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. *Land Value* is the dollar value of farmland per acre, in real (2010) dollars, and is winsorized at the 0.1 percent level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley 2008), as indicated. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). The crisis period is defined from 1981-1987 in columns 1 and 2, and from 1984-1987 in column 3; the non-crisis period runs from 1950-1980 and 1988-2010; the full sample runs from 1950 to 2010.

Dependent Variable: log(*Land Value*)

	(1)	(2)	(3)	(4)
Time Period:	Crisis, 1981-1987		Crisis, 1984-1987	Non-crisis
Days Above 83	-0.031***	-0.004***	-0.008***	-0.001
	(0.008)	(0.001)	(0.002)	(0.001)
Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes
Standard Errors	Spatial	Spatial	Spatial	Spatial
Observations	693	693	396	5,339
R^2	0.71	0.996	0.99	0.98

Table 4: Temperature Shocks, Instrumental Variable Regressions during the Crisis

This table provides instrumental variable regression results for the effects of temperature shocks on corn yields and land values during the farm debt crisis. 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, in real (2010) dollars. *Corn Yield* and *Land Value* are winsorized at the 0.1 percent level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. $\widehat{\log(Yield)}$ is instrumented log corn yield. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported).

	(1)	(2)	(3)	(4)
Time Period:	1981-1987		1984-1987	
IV Stage:	First Stage	Second Stage	First Stage	Second Stage
Dependent Variable:	log(*Corn Yield*)	log(*Land Value*)	log(*Corn Yield*)	log(*Land Value*)
Days Above 83	-0.033***		-0.022***	
	(0.006)		(0.007)	
$\widehat{\log(Yield)}$		0.120***		0.339***
		(0.032)		(0.047)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	693	693	396	396
R^2	0.80	0.996	0.75	0.99

Table 5: Agricultural Loan Delinquencies and Bank Failures

This table provides second-stage instrumental variable regression results for the effects of temperature shocks on bank failure rate during the farm debt crisis and non-crisis years. All variables represent county-level values in the indicated year. *Ag Delinquencies* is the outstanding balance of agricultural loans that are 90 days or more past-due and upon which the bank continues to accrue interest, in real (2010) dollars, and is winsorized at the 0.1 percent level. *Bank Failure* is a dummy variable that takes a value of 1 if there was a bank failure in the given year, and 0 otherwise. *Bank Failure Crisis* is a dummy variable which takes a value of 1 if there was a bank failure from the given year until the end of the crisis, and 0 otherwise. $\log(\widehat{Yield})$ is instrumented log corn yield. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). Panel A runs from 1984 to 1987, the peak of the farm debt crisis, while Panel B runs from 1988-2000 for column 1 and from 1950 to 1980 and 1988-2010 for column 2, periods outside the farm debt crisis.

Panel A: Crisis

	(1)	(2)	(3)
Dependent Variable:	log(*Ag Delinquencies*)	*Bank Failure*	*Bank Failure Crisis*
$\log(\widehat{Yield})$	-3.249***	-0.324**	-0.402***
	(0.835)	(0.144)	(0.064)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	396	396	396
R^2	0.50	0.24	0.74

Panel B: Non-Crisis

	(1)	(2)
Dependent Variable:	log(*Ag Delinquencies*)	*Bank Failure*
$\log(\widehat{Yield})$	-0.707	0.015
	(1.276)	(0.022)
Year FE	Yes	Yes
County FE	Yes	Yes
Observations	1,273	5,339
R^2	0.38	0.04

Table 6: Agricultural Wages and Employment

This table provides second-stage instrumental variable regression results for the effects of temperature shocks on agricultural wages and employment during the farm debt crisis and non-crisis years. All variables represent county-level values in the indicated year. *Ag Employment* is the total employment in agricultural crop production. *Ag Avg Wage* is the average annual wage for an individual in agricultural crop production. *Ag Total Wages* is the sum total of all wages for agricultural crop production. $\log(\widehat{Yield})$ is instrumented log corn yield. Outcome variables are winsorized at the 0.1 percent level. All dollar amounts are in real (2010) dollars. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). Panel A runs from 1984 to 1987, the peak of the farm debt crisis, while Panel B runs from 1975-1980 and from 1988-2000, the period outside the farm debt crisis.

Panel A: Crisis

	(1)	(2)	(3)
Sector:	Agricultural Crop Production		
Dependent Variable:	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)
$\log(\widehat{Yield})$	29.95**	2.87**	4.37**
	(14.72)	(1.36)	(2.01)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	396	396	396
R^2	0.66	0.75	0.74

Panel B: Non-Crisis

	(1)	(2)	(3)
Sector:	Agricultural Crop Production		
Dependent Variable:	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)
$\log(\widehat{Yield})$	-6.69	1.14	1.42
	(7.04)	(0.92)	(1.18)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	1,875	1,875	1,875
R^2	0.38	0.44	0.45

Table 7: Wages and Employment in the Services Sector

This table provides second-stage instrumental variable regression results for the effects of temperature shocks on wages and employment in the services sector during the farm debt crisis and non-crisis years. All variables represent county-level values in the indicated year. *Services Employment* is the total employment in the service sector. *Services Avg Wage* is the average annual wage for an individual in the service sector. *Services Total Wages* is the sum total of all wages for the service sector. $\log\widehat{(Yield)}$ is instrumented log corn yield. Outcome variables are winsorized at the 0.1 percent level. All dollar amounts are in real (2010) dollars. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). Panel A runs from 1984 to 1987, the peak of the farm debt crisis, while Panel B runs from 1975-1980 and from 1988-2000, the period outside the farm debt crisis.

Panel A: Crisis

	(1)	(2)	(3)
Sector:	Service Sector		
Dependent Variable:	*Services Employment*	log(*Services Avg Wage*)	log(*Services Total Wages*)
$\log\widehat{(Yield)}$	-720.71***	0.075**	-0.002
	(106.57)	(0.033)	(0.05)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	396	396	396
R^2	0.997	0.969	0.998

Panel B: Non-Crisis

	(1)	(2)	(3)
Sector:	Service Sector		
Dependent Variable:	*Services Employment*	log(*Services Avg Wage*)	log(*Services Total Wages*)
$\log\widehat{(Yield)}$	-183.72	-0.001	-0.05
	(710.80)	(0.025)	(0.067)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	1,875	1,875	1,875
R^2	0.919	0.858	0.986

Table 8: Services Employment and Dependence on Farm Income

This table provides regression results for the effects of temperature shocks on service sector employment, and how the magnitude of the effect varies based on the county's dependence on farm income during the crisis. Panel A runs an interaction regression with a measure of farm dependence, while Panel B separates the sample into counties with either high or low farm dependence and runs instrumental variable specifications for each (second-stage results are provided). All variables represent county-level values in the indicated year. *Services Employment* is the total employment in the service sector. *Services Avg Wage* is the average annual wage for an individual in the service sector. Outcome variables are winsorized at the 0.1 percent level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. *Farm Income Pct* is percentage of total county income that is comprised of farm crop income, taken as an average from 1969-1980. $\widehat{\log(Yield)}$ is instrumented log corn yield. All regressions are run from 1984-1987. Standard errors are given in parentheses, and are corrected for spatial correlation in Panel A (as in Conley, 2008). *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported).

Panel A: Interaction with Dependence on Farm Income

	(1)	(2)
Dependent Variable:	*Services Employment*	log(*Services Avg Wage*)
Days Above 83	55.91***	-0.003***
	(21.59)	(0.0002)
Days Above 83	-234.72***	0.008
× *Farm Income Pct*	(81.84)	(0.007)
Year FE	Yes	Yes
County FE	Yes	Yes
Standard Errors	Spatial	Spatial
Observations	396	396
R^2	0.997	0.963

Panel B: Instrumental Variable Regressions

	(1)	(2)	(3)	(4)
	Below-Median Farm Income Dependence		Above-Median Farm Income Dependence	
Dependent Variable:	*Services Employment*	log(*Services Avg Wage*)	*Services Employment*	log(*Services Avg Wage*)
$\widehat{\log(Yield)}$	-667.17**	0.105***	66.87*	0.042
	(272.54)	(0.037)	(37.11)	(0.067)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	196	196	200	200
R^2	0.997	0.976	0.992	0.916

Table 9: Effects Based on Bank Balance Sheets

This table provides second-stage instrumental variable regression results for the effects of temperature shocks on the outcome variables during the crisis years, splitting the sample based on the aggregate loan-to-deposit ratio of the banking market. High (Low) Loan-to-Deposit Counties are counties that are above (below) the median in terms of their mean (from 1975 to 1980) aggregate loans/deposits for banks in the county. All variables represent county-level values in the indicated year, and all outcome variables except *Bank Failure* are winsorized at the 0.1 percent level. $\log(\widehat{Yield})$ is instrumented log corn yield. All dollar amounts are in real (2010) dollars. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). All regressions are run from 1984 to 1987.

Panel A: High Loan-to-Deposit Counties

Dependent Variable:	log(*Land Value*)	log(*Ag Delinquencies*)	*Bank Failure*	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)	*Services Employment*	log(*Services Avg Wage*)
$\log(\widehat{Yield})$	0.407***	-3.815**	-0.340	49.648**	6.158***	9.264***	-7.012	0.051*
	(0.075)	(1.628)	(0.299)	(21.707)	(1.337)	(2.154)	(80.807)	(0.028)
Year, County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	200	200	200	200	200	200	200	200
R^2	0.98	0.45	0.25	0.73	0.78	0.76	0.996	0.97

Panel B: Low Loan-to-Deposit Counties

Dependent Variable:	log(*Land Value*)	log(*Ag Delinquencies*)	*Bank Failure*	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)	*Services Employment*	log(*Services Avg Wage*)
$\log(\widehat{Yield})$	0.292***	-2.594**	-0.245	14.483	0.404	0.761	-1393.723***	0.103
	(0.025)	(1.280)	(0.162)	(10.256)	(1.192)	(1.634)	(196.526)	(0.074)
Year, County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196	196	196
R^2	0.99	0.52	0.23	0.53	0.73	0.73	0.997	0.96

Table 10: Temperature Shocks and County Income

This table provides regression results for the effects of temperature shocks on county income per capita. Columns 1 and 2 provide results from an instrumental variable specification, while Columns 3 and 4 provide reduced-form results. All variables represent county-level values in the indicated year. log(*Income*) is log income-per-capita (in real 2010 dollars), and is winsorized at the 0.1 percent level. $\widehat{\log(Yield)}$ is instrumented log corn yield. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. The crisis period runs from 1984 to 1987, the peak of the farm debt crisis. The non-crisis period includes 1969-1980 and 1988-2010. Standard errors are given in parentheses and are clustered at the year level in Columns 1 and 2 and are corrected for spatial correlation (as in Conley, 2008) in Columns 3 and 4 as indicated. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported).

Dependent Variable: log(*Income*)

	(1)	(2)	(3)	(4)
Time Period:	Crisis	Non-crisis	Crisis	Non-crisis
$\widehat{\log(Yield)}$	0.138***	0.036		
	(0.051)	(0.030)		
Days Above 83			-0.003***	-0.001
			(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Standard Errors	Robust	Robust	Spatial	Spatial
Observations	396	3,557	396	3,557
R^2	0.95	0.95	0.94	0.95

Table 11: County Income and Dependence on Farm Income

This table provides regression results for the effects of temperature shocks on county income per capita, and how the magnitude of the effect varies based on the county's dependence on farm income during the crisis. Panel A runs an interaction regression with a measure of farm dependence, while Panel B separates the sample into counties with either high or low farm dependence and runs instrumental variable specifications for each (second-stage results are provided). All variables represent county-level values in the indicated year. log(*Income*) is log income-per-capita (in real 2010 dollars), and is winsorized at the 0.1 percent level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. *Farm Income Pct* is percentage of total county income that is comprised of farm crop income, taken as an average from 1969-1980. $\log(\widehat{Yield})$ is instrumented log corn yield. All regressions are run from 1984-1987. Standard errors are given in parentheses, and are corrected for spatial correlation in Panel A (as in Conley, 2008). *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported).

Panel A: Interaction with Dependence on Farm Income

	(1)
Dependent Variable:	log(*Income*)
Days Above 83	-0.001
	(0.001)
Days Above 83	-0.010*
× *Farm Income Pct*	(0.006)
Year FE	Yes
County FE	Yes
Standard Errors	Spatial
Observations	396
R^2	0.94

Panel B: Instrumental Variable Regressions

	(1)	(2)
	Below-Median Farm Income Dependence	Above-Median Farm Income Dependence
Dependent Variable:	log(*Income*)	log(*Income*)
$\log(\widehat{Yield})$	0.123***	0.188**
	(0.026)	(0.094)
Year FE	Yes	Yes
County FE	Yes	Yes
Observations	196	200
R^2	0.98	0.92

Figure 1: Distribution of Temperature Shocks

This figure shows the distribution of temperature shocks during the growing season, for the entire sample from 1950 to 2010. The vertical axis represents the density, while the horizontal axis gives the number of days in the growing season for a given county-year that were above 83°F.

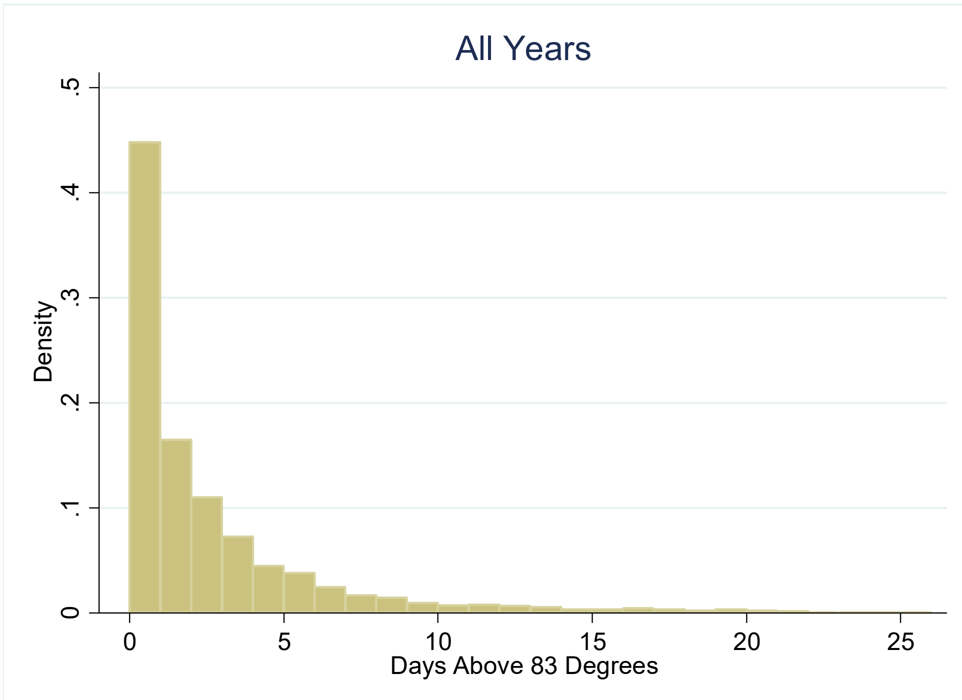


Figure 2: Distribution of Temperature Shocks in Excess of Averages

This figure shows the distribution of temperature shocks during the growing season, in excess of county and yearly averages, for the entire sample from 1950 to 2010. The vertical axis represents the density, while the horizontal axis gives the de-meaned number of days in the growing season for a given county-year that were above 83°F.

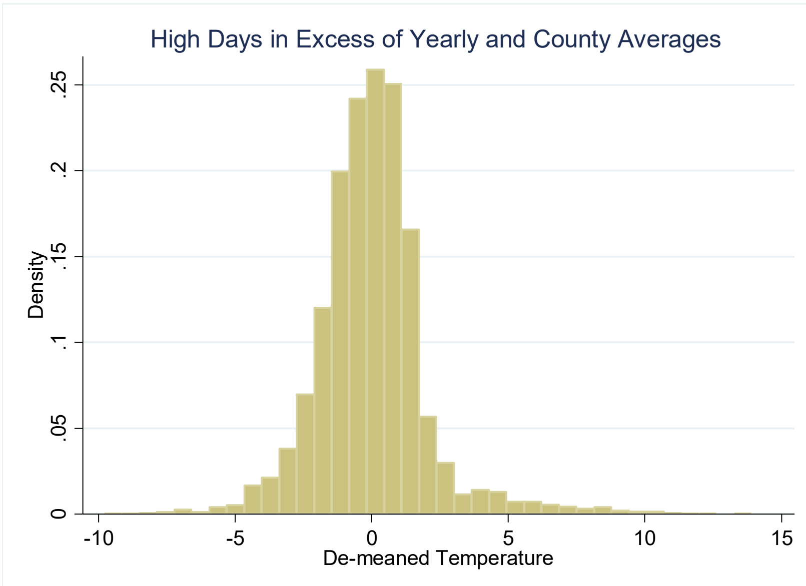


Figure 3: Distribution of Temperature Shocks in Different Years

This figure shows the distribution of temperature shocks during the growing season, for various years. In each graph, the vertical axis represents the density, while the horizontal axis gives the number of days in the growing season for a given county in the indicated year that were above 83°F.

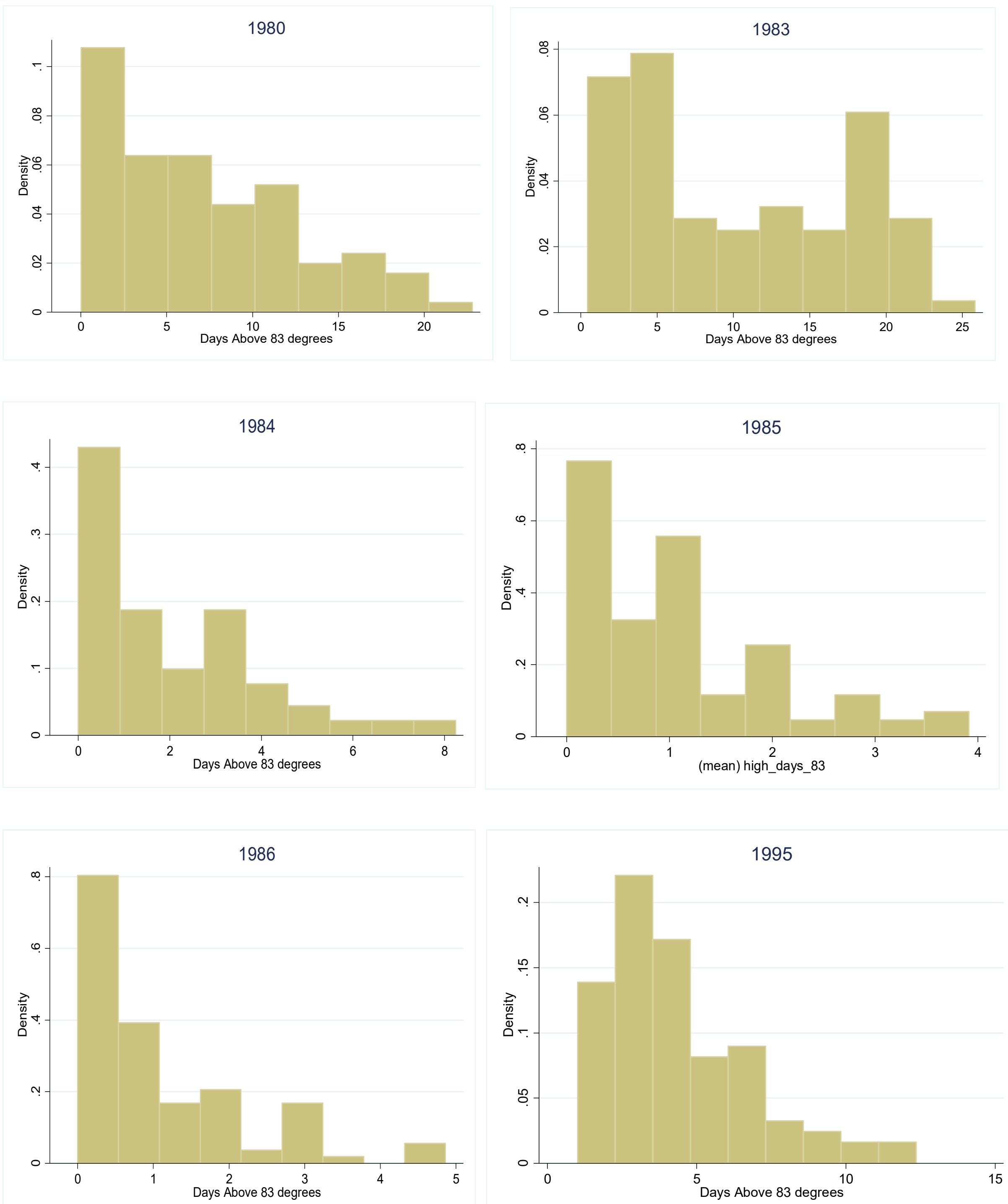


Figure 4: Corn Yields, Farm Land Values, and Agricultural Debt over Time

This figure depicts average corn yields, land values, and agricultural debt over time. Each data point is an average across all counties in Iowa. Corn yield is defined as bushels of corn produced per acre of harvested land. Land Value is the dollar value of farmland per acre, in real (2010) dollars. Total agricultural debt is the sum of agricultural loans to finance production and real estate debt secured by farmland, in real (2010) dollars.

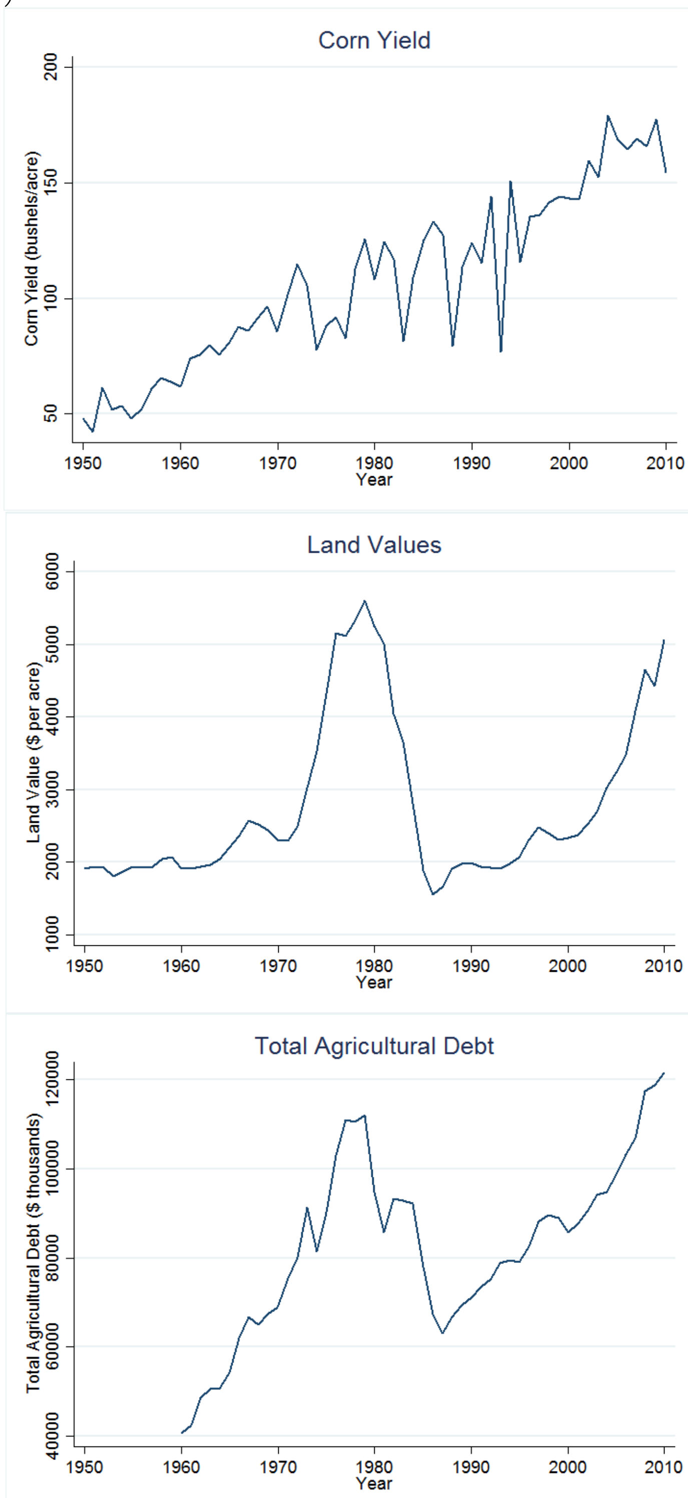
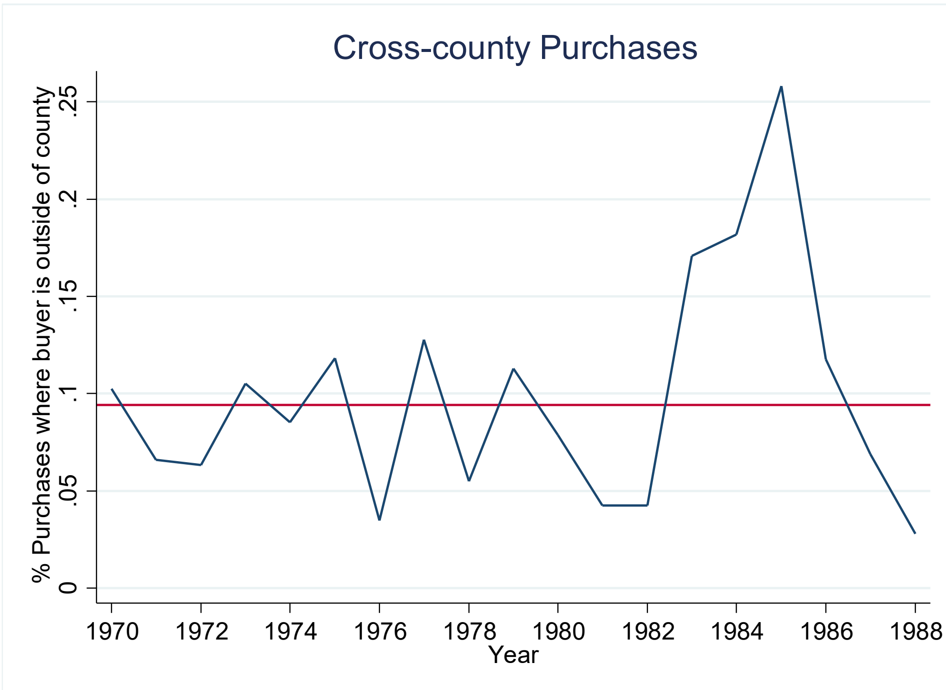


Figure 5: Cross-county Land Purchases in Hamilton County

This figure depicts cross-county land purchases in Hamilton County – purchases where the buyer is located outside of the county. The red horizontal line indicates the mean over the sample period.



Appendix

Table A1: Main Results, Weighted by County Corn Acres

This table provides second-stage instrumental variable regression results for the effects of temperature shocks on the outcome variables during the crisis and non-crisis years, but weighting by acres of corn planted in each county. All variables represent county-level values in the indicated year, and all outcome variables except *Bank Failure* are winsorized at the 0.1 percent level. $\log(\widehat{Yield})$ is instrumented log corn yield. All dollar amounts are in real (2010) dollars. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported). Panel A runs from 1984 to 1987, the peak of the farm debt crisis, while Panel B runs regressions during the non-crisis, defined depending on data availability as in the main text.

Panel A: Crisis

Dependent Variable:	log(*Land Value*)	log(*Ag Delinquencies*)	*Bank Failure*	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)	*Services Employment*	log(*Services Avg Wage*)	log(*Services Total Wages*)	log(*Income*)
$\log(\widehat{Yield})$	0.344***	-3.257***	-0.337**	30.245**	2.949**	4.495**	-730.395***	0.075**	-0.0003	0.138***
	(0.050)	(0.796)	(0.151)	(14.982)	(1.393)	(2.057)	(104.920)	(0.032)	(0.046)	(0.051)
Year, County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396	396	396	396	396
R^2	0.99	0.50	0.24	0.66	0.75	0.74	0.997	0.97	0.998	0.95

Panel B: Non-Crisis

Dependent Variable:	log(*Land Value*)	log(*Ag Delinquencies*)	*Bank Failure*	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)	*Services Employment*	log(*Services Avg Wage*)	log(*Services Total Wages*)	log(*Income*)
$\widehat{\log(Yield)}$	0.051	-0.729	0.015	-6.566	1.191	1.501	-183.702	-0.002	-0.053	0.037
	(0.049)	(1.243)	(0.022)	(7.250)	(0.932)	(1.193)	(704.986)	(0.025)	(0.065)	(0.030)
Year, County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,339	1,273	5,339	1,875	1,875	1,875	1,875	1,875	1,875	3,557
R^2	0.98	0.37	0.04	0.38	0.43	0.45	0.92	0.86	0.99	0.95

Table A2: Services Employment and Dependence on Farm Income

This table provides regression results for the effects of temperature shocks on service sector employment, and how the magnitude of the effect varies based on the county's dependence on farm income during the crisis. All variables represent county-level values in the indicated year. *Corn Yield* is defined as bushels of corn produced per acre of harvested land. *Services Employment* is the total employment in the service sector. Outcome variables are winsorized at the 0.1 percent level. *Days Above 83* is the number of days where the average temperature is above 83°F during the growing season. *Farm Income Pct* is percentage of total county income that is comprised of farm crop income, taken as an average from 1969-1980. $\widehat{\log(Yield)}$ is instrumented log corn yield. The county fixed effects are not interacted with the fraction of agricultural income importance indicator variable since the indicator variable, similar to the sample split, is based off of the fraction of pre-crisis agricultural income, and does not vary over time within a given county. All regressions are run from 1984-1987. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively. All regressions include an intercept term (not reported).

IV Stage:	First Stage	Second Stage
Dependent Variable:	log(*Corn Yield*)	*Services Employment*
Days Above 83	-0.022**	
	(0.011)	
$\widehat{\log(Yield)}$		-404.711**
		(160.425)
Year FE	Yes	Yes
Year FE × *High Farm Income Dummy*	Yes	Yes
County FE	Yes	Yes
Observations	396	396
R^2	0.766	0.997