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 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, and the probability of bank failure. Further, we measure how cash injections affect local labor markets, analyzing the impact on employment and wages both within and outside of the sector receiving a positive cash flow shock. 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

The role of interventions meant to strengthen firm balance sheets during a financial crisis is a much discussed and debated question. For instance, during the 2008-2009 financial crisis, there was substantial debate regarding the effectiveness of the Stimulus Bill, which reduced firms' tax obligations and in so doing provided cash injections to the real sector. In the presence of financial frictions, weak firm balance sheets detrimentally affect economic activity, and so such cash injections could serve to mitigate the extent of a crisis. Furthermore, cash injections could not only have an effect on firms receiving the intervention, but also generate spillovers to other firms as well as to households.

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, our identification strategy relies on exploiting variation arising from random weather shocks to analyze the general equilibrium effects of cash flow variation during the crisis. As a large literature in agronomics shows, weather shocks affect crop yields and hence farm income. Geographic differences in weather thus provide plausibly exogenous variation in local cash flow and are akin to aggregate cash injections to all the farms that operate within a county. 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.

The 1980s farm debt crisis was similar in many ways to the 2008-2009 recession. The crisis was preceded by large increases in both farm real estate debt as well as agricultural land prices. Subsequently, during the crisis, land prices plummeted by nearly 50 percent. The farming sector was in disarray with numerous agricultural banks failing throughout the period.[1]

[1] For studies of the farm debt crisis see e.g. Calomiris, Hubbard, and Stock, 1986.

As a first step in our analysis, we use data on weather shocks and confirm that county-level weather variation is related to farm yields. We focus on corn production in Iowa and use the fact that corn yields are highly sensitive to small changes in temperature, with excessive heat reducing yields. We measure how temporary shocks in weather during the corn growing season affect yields, and consistent with the agronomics literature, find economically significant effects.

Since variation in local weather affects yields, weather shocks provide exogenous variation in local cash flows and balance sheets 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. 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 since external finance is often prohibitively costly or unavailable. An inability to smooth shocks during a crisis is predicted, therefore, to translate to a host of market outcomes, both real and financial. We empirically show that this was indeed the case: a (weather-driven) reduction in firms' cash positions within a county during the crisis did indeed have detrimental general equilibrium effects on land markets, the financial sector, labor markets, and ultimately, county per-capita income.

We start by examining the effect of cash-flow driven weather shocks on agricultural land prices. We expect that during a financial crisis, increases in cash available to firms will increase asset prices through a liquidity pricing effect, as in Shleifer and Vishny (1992) and Allen and Gale (1994). When financial frictions are high, the amount of funds available to firms will tend to affect asset prices, as economic agents cannot raise external finance to bring prices to fundamental value. As in all models of liquidity 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. 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 with a hand-gathered, micro-level dataset of land transaction records.

We examine the effect of cash flow shocks on asset prices by exploiting county-level weather variation. We first show that land prices are indeed negatively related to exogenous county-level temperature shocks. 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). The results show that counties that receive a negative weather shock—in that temperature during the growing season was high—do indeed exhibit lower land values. To understand the economic magnitude of this effect, we utilize an instrumental variables (IV) strategy in which, as a first stage, we instrument county-level yields with the weather shock variable, and as a second stage, we relate land prices to (predicted) yields. The results show that the elasticity of land prices to yields is 0.33. Cash flow injections during the farm debt crisis thus had a significant effect on land prices. To our knowledge, this is the first paper that provides causal evidence of cash-in-the-market pricing.[2]

As a placebo test, we rerun our analysis but focus on the period outside of the crisis. The reduced financial frictions and stronger farm balance sheets outside of the crisis would predict that land values are less sensitive to cash flow shocks in this period. This is exactly what the results show. Outside of the crisis there is no statistically significant relation between land values and weather shocks, or between land values and farm yields (as instrumented with weather shocks).

We continue our analysis by examining the relation between cash flow injections, loan delinquencies, and bank failures. Once again, our main strategy is to exploit weather shocks to generate variation in local farm cash flows. Using the IV strategy described above, we first show that during the crisis, counties that experience reduced average yields due to bad weather shocks exhibit

[2] For theoretical contributions on cash-in-the-market pricing see Allen and Gale (1994, 1998), Shleifer and Vishny (1992), Kiyotaki and Moore (1997).

higher agricultural loan delinquencies. As would be predicted, farms in these counties find it more difficult to repay their obligations.

We then analyze how temporary cash flow variation during the crisis affects financial intermediaries. To do so, we relate county crop yields, as instrumented by weather shocks, to county bank failures. During financial crises, temporary shocks to borrowers that translate into higher delinquencies may also filter through and affect banks. As a result, we expect cash flow variation at the borrower-level to translate into financial distress at the bank-level. This is what the results indicate: during the crisis, counties that experience higher crop yields due to favorable weather shocks exhibit lower bank failure rates. 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. When financial frictions are high and firms' ability to smooth shocks is limited, temporary cash flow shocks thus appear to propagate into the financial sector in the form of bank failure rates.[3] Banks thus appear unable to smooth temporary shocks to their balance sheets during the debt crisis, consistent with the existence of financial constraints and an external finance premium, at the *bank* level.[4]

We next turn to the effect of cash flow injections during crises on labor markets. We begin by focusing on the agricultural labor market and then turn to examining spillovers into labor markets in other sectors. Our main hypothesis is that firms in the crisis find it difficult to smooth temporary cash flow shocks and, as part of their response, will reduce their labor workforce.[5] Consistent with this view, we find that counties that experience a negative weather-driven cash flow shock during the

[3] 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.
[4] For an analysis of the implications of financial constraints at the bank level, see Bernanke and Blinder (1988) and the literature on the bank-lending channel of monetary policy.
[5] Chodorow-Reich (2014) examines the effect of bank lending frictions on employment outcomes using the dispersion of lender health following the Lehman crisis to generate variation in credit supply.

crisis exhibit lower agricultural employment rates.[6] We find that these counties also exhibit a reduction in average county agricultural wages, consistent with an inward shift in the effective labor demand.[7] Next, 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, consistent with firms' greater ability to smooth shocks during these periods either by relying on internal funds or on available external finance. The results thus show that during the debt crisis, when financial frictions were high, temporary cash flow shocks translated into labor market disruptions in the agricultural sector.

We next examine labor market spillover effects of cash flow shocks in the agriculture sector on the service sector.[8] We find that during the crisis, negative cash flow shocks in the agricultural sector are related to employment increases and average wage decreases in the local service sector. Workers appear to leave the agriculture sector following a temporary negative cash flow shock, reallocating towards the service sector. Consistent with an increase in labor supply in services, we find that average wages in the service sector then declines.

We hypothesize that the labor market spillover effect of local cash flow shocks in agriculture on service sector employment depends on the share of agriculture within the local economy. When the agriculture sector is large within a county, reductions in employment within agriculture following a cash flow shock in that sector should tend to reduce demand, and hence employment, in other sectors as well. 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 dominant, during the financial crisis cash flow shocks in agriculture reduce employment within the

[6] As usual, all regressions are run with county and year fixed effects, implying that the results refer to the relation between changes in employment and the weather shocks, net of the county means of both variables and common year effects.
[7] We cannot, though, rule out a compositional effect in which higher wage workers are fired following a negative shock. This would of course, still be consistent with the main hypothesis that cash flow shocks create labor market disruptions.
[8] When we examine wages and employment in manufacturing, we do not find any significant effects.

service sector. Thus, during a debt crisis, firms' inability to smooth cash flow shocks is transmitted into other industries located within the same area, as employees are dislocated within the economy.

The results above show how county-level cash flow shocks during the crisis had a significant economic affect on a host of real outcomes across numerous 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 temporary cash flow shocks ultimately affected county-level income during the financial crisis. Using local weather shocks to obtain exogenous variation in county level cash flow, we calculate the local-level cash-flow to income multiplier. 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 (weather-driven) cash flow shocks and county income levels. The size of the multiplier is thus state dependent, and larger during crises.[9] As a final result, we show that during the debt crisis, larger cash injections exhibit greater effects on income levels, suggesting a convex relation between cash-flow injections during the crisis and the income multiplier.

Taken together, our results show how, in a debt crisis, temporary shocks to firm cash flows can have important effects on a host of real and financial outcomes. Consistent with the presence of high financial frictions during debt crises, firms are unable to smooth short-term negative shocks to their cash balances. When cash balances are reduced, asset prices decline, delinquency rates rise, banks are more likely to fail, labor market disruptions ensue, and income levels decline. Conversely, increased cash balances during the crisis improved conditions in local land markets, 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 exploits local-level variation by examining the effect of state-level fiscal policy on employment. Nakamura and Steinsson (2014) estimate government spending multipliers using variation driven by military procurement. Also of relevance is the literature on fiscal policy at the zero lower bound (e.g. Krugman, 1998; Eggertsson and Woodford, 2003; and Christiano, Eichenbaum, and Relebo, 2011).

markets, and labor markets, and ultimately raised income levels. Viewed from the perspective of policy, 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 smoothing short-term shocks.

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 prices, Section 3.3 focuses on the relation of cash flow shocks during the crisis on the banking sector, Section 3.4 analyzes the effect of cash flow shocks on labor markets, focusing on employment and wages, while Section 3.5 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 involves using 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 Dell, Jones, and Olken, 2014, for a review). This variation is plausibly exogenous to farm-level activity, certainly within the frequency we study.

Our empirical 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 terms of the production of corn, which is the most plentiful U.S. crop and which is also

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

well understood in terms of its growth response to temperature fluctuations. Finally, agricultural data for Iowa are available at a more detailed level and for a much longer time period compared to other states, allowing for a more complete time series of our empirical tests.[11]

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, financial intermediation, labor etc. In doing so, we rely on prior work that has found that exposure to temperatures above a certain threshold during the corn growing season—the months from April through September—are harmful for corn yields (see e.g. Schlenker and Roberts, 2006, 2009). Figure 1, taken from Schlenker and Roberts (2006), demonstrates this negative effect of high temperatures on corn yields. Following this literature, we measure county-level cumulative exposure to harmful temperature with the number of days in the growing season with average temperature above 83°F, a threshold corresponding to that identified in the literature.[12] Annual corn yields at the county level are then instrumented with this number of above 83°F days. The first-stage regression that we run is thus given by:

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

where *Corn Yield* is measured in bushels per acre and *Days Above 83* is the number of days in the corn growing season which have an average temperature above 83 degrees Fahrenheit. 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 take into account time-invariant omitted characteristics at the county level (like soil quality), or county-invariant shocks. Our second-stage regression specification examines the effect of instrumented corn yields, given by (1), on various outcome variables:

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[11] Farmland values are only available for Agricultural Census years (at five-year intervals) for most other states.

[12] Schlenker and Roberts (2009) note that temperature becomes harmful past 28°C.

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

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 using harmful temperature as an instrument via regression (1), δ_t are county fixed effects, and γ_i are year fixed effects.[13] The outcomes that we examine are county-level agricultural land values, agricultural loan delinquencies, bank failures, wages, employment, and income. The exclusion restriction underlying the identification strategy is that temperature only affects the outcome variables in (2) through its effect on corn yields (and through yields, farm cash flow). As discussed below, in support of this assumption we do not find any effects of weather shocks on the outcome variables—despite having an effect on yields—in non-crisis periods when financing frictions are less likely to bind.

2.2 Data Sources

We construct a novel dataset of county-level outcome variables in Iowa using a variety of different 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, for each weather station we calculate the number of days in the corn growing season (from April to September) where the average daily temperature is above 83 degrees Fahrenheit.[14] We then construct county-level estimates of this temperature measure for Iowa using the procedure of Deschênes and Greenstone (2012). Using geographical data for each county in Iowa from the U.S. Census Bureau, we construct a county-level estimate of the number of hot days in the growing season by using a weighted average of all weather station estimates within a 50km radius of the

[13] We cluster our standard errors at the year-level, in order to account for spatial correlation between counties. In particular, by clustering at the year-level we are assuming that *all* counties in Iowa are correlated regardless of their distance to one another, which is a stronger assumption than a typical spatial correlation adjustment of standard errors (e.g. Conley (1999)) which assumes that the correlation decays with distance.
[14] In any given year, we only use weather stations that have non-missing data for every day in July.

geographical center of each county. The weights are the inverse of the squared distance from each weather station to the geographical center of the county. As there are 99 counties in Iowa, this yields a total of 6,032 county-year temperature observations for the sample period from 1950 to 2010, and 693 observations for the crisis period from 1981 to 1987.

Our measure of corn yields come from the USDA's National Agricultural Statistics Service (NASS) yearly crop surveys. The NASS provides yearly data at the county level of average corn yields from 1950 to 2010, measured in bushels per acre harvested.

Our measure of farmland values come from the Iowa State University Farmland Value Survey, which provides yearly county-level estimates (as measured in November of each calendar year) of the average value per acre of Iowa farmland from 1950 to 2010.[15] The respondents to the survey are individuals that are considered to be knowledgeable of land market conditions, such as agricultural real estate brokers. In each year, respondents are asked to provide their estimate of current farmland prices in the county they are located. Studies have shown that these survey values closely track actual land sales prices (see Stinn and Duffy, 2012, and Kuethe and Ifft, 2013).

We use two different data sources to examine the effect of shocks on banks. The first source is data on agricultural loan delinquencies from the Federal Reserve's Commercial Bank Data Call Reports. This is defined as the outstanding balance of agricultural loans that are 90 days or more past-due and upon which the bank continues to accrue interest, which is available from 1984 to 2000. The second source is data on bank failures for each county, taken from the Federal Deposit Insurance Corporation (FDIC). The data on bank failures run from 1984 to 2010. In order to properly attribute the effects of temperature shocks during the growing season to bank failures, a bank failure is defined as occurring in a given year if it happened within the period from the end of

[15] 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 roughly 2.6% of total Iowa farmland was irrigated in 2012.

the growing season in that year (October and onwards) through the growing season of the following year (September and earlier).

Finally, we collect data on wages and employment from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages. We take data on county-level employment, average annual wages, total (aggregate) wages, and number of establishments for the period from 1975 to 2000. We collect these data items for the agricultural crop production sector, as well for other sectors in order to show spillover effects.[16]

2.3 The Farm Debt Crisis

As in many financial crises, the period preceding the farm debt crisis in the 1980s saw sharp increases in debt and land prices. In the 1970s, increasing commodity prices along with an expansion in exports led to increased farm production, financed by debt. Between 1971 and 1980, agricultural exports roughly doubled, farmland values rose by 88 percent and farm debt rose by 66 percent (see Calomiris, Hubbard, and Stock, 1986).

The farm debt crisis was triggered in the early 1980s by the combination of a sharp increase in interest rates undertaken by the Federal Reserve under Paul Volcker and Russia's imposition of an embargo on U.S. agricultural imports. The result was a period of severe financial distress for farmers, leading to significantly weaker farm balance sheets, sharp drops in farmland values, and an erosion in farm credit conditions. Across the U.S., the average value of farmland dropped by 29% between 1980 and 1984; delinquent loans rose to 7.5% of total loans at small agricultural banks by 1985; and there were 100 small agricultural bank failures in 1984 and 1985, an increase from 7 in 1983 (see Calomiris, Hubbard, and Stock, 1986). These effects were even more pronounced in the

[16] 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). The caveat with our agricultural wage and employment data is that the Quarterly Census of Employment and Wages only covers larger farms—it does not cover most agricultural workers on small farms or self-employed agricultural workers.

U.S. Corn Belt states, with their significant agricultural sectors. For example, in Iowa, farmland prices dropped by an average of 46% across all counties. Iowa alone experience 39 commercial bank failures between 1981 and 1987.

2.4 Summary Statistics

Table 1 presents the summary statistics of the main variables. During the crisis, the average number of days in the growing season where the average temperature exceeds 83 degrees Fahrenheit is 2.4. The overall standard deviation of days with temperature above 83 degrees Fahrenheit is roughly 3 days, indicating a fair amount of variability. As expected, the number of days above 83 degrees Fahrenheit does not differ substantially from that during the crisis (panel B). Figure 2 reports the density plots of the distribution of days above 83 degrees Fahrenheit over our entire sample. As our main specifications include county and year fixed effects, Figure 2 exhibits variation which we do not exploit in our identification strategy. Figure 3, therefore, presents density plots of temperature variation demeaned with year and county fixed effects. The distribution of demeaned days above 83 degrees Fahrenheit is symmetric around zero, but also exhibits substantial variation. The density plots for the individual years (Figure 4) 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 degrees Fahrenheit.

The mean corn yield for counties in Iowa in our sample is roughly 124 bushels per acre of land harvested during the crisis. Mean corn yields have increased over time from a value of 48.1 bushels per acre in 1950 to a value of 154.6 bushels per acre in 2010, consistent with technological improvements in the sector. The mean (real) value per acre of farmland during the crisis, defined as the years from 1984 to 1987, is $2,000 per acre. However, during this time period farmland prices dropped by an average of 46% across all counties. Figure 5 depicts the evolution of average corn yield, land value, and agricultural debt across all counties for each year in the sample. Average corn yield increases over the sample period 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, suggesting that changes in land productivity were not the primary driver of the large decline in farmland prices. Finally, agricultural debt increases steadily from 1960 to 1980 but drops significantly during the farm debt crisis, as would be expected by a deleveraging process common in financial crises.

3 Empirical Results

As explained in Section 2, we analyze the effect of cash flow injections during a crisis by exploiting variation in weather shocks across counties and over time in Iowa. These weather shocks, and the associated effect on corn yields, provide an exogenous source of variation in cash flow, and hence firm balance sheets, during the crisis.

3.1 Weather Shocks and Crop Yields

In measuring weather shocks, we follow the agricultural economics literature that has shown how high temperature during the growing season—from April through September—adversely affects corn yields. We thus 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 degrees Fahrenheit. This temperature threshold is taken from

Schlenker and Roberts (2009), although our results our robust to alternate definitions of high temperature values.[17]

As a first step in the analysis, we run the following reduced-form specification that relates yields and land values to weather shocks:

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

where $Y_{i,t}$ is either corn yields (bushels of corn produced per acre) or farm land values in county i in year t, and *Days Above 83* is the weather shock measure capturing hot average-temperature years, as described above. All regressions include a vector of year fixed effects, δ_t, and most also include a vector of county fixed effects, η_i. Following the literature in agronomics (e.g. Deschênes and Greenstone, 2007, Schlenker and Roberts 2006, 2009), standard errors are calculated correcting for spatial correlation as in Conley (2008).

Table 2 reports the results for corn yields, running 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. As can be seen in Column (2), adding county fixed effects does not substantially change the results. Interpreting the coefficient, adding an extra day during the growing season with an average temperature above 83 reduces corn yields by 3.3 percent. While seemingly high, this result is in line with much prior work in the literature such as Schlenker and Roberts (2009). Corn is extremely sensitive to high temperature values during the growing season—an established fact in the agronomics literature that is at the heart of our identification strategy. It is important to emphasize that the variation we exploit for identification is not periods of drought or extreme heat throughout the growing season, but variation in temperature

[17] Specifically, Schlenker and Roberts (2009) note that for the geographical region that Iowa is located in, temperature becomes harmful past 28°C or 29°C (82.4°F or 84.2°F). We thus use 83°F as our threshold.

across counties, with some experiencing a number of days in the growing season where the average temperature is above 83 degrees Fahrenheit.

In Column 3, we report the results for the period of 1984 to 1987—the peak of the farm debt crisis—and find similar results. In Column 4 we estimate the results for the non-crisis periods and find again that the estimated coefficients are very similar to those during the crisis. The effect of weather on yields is biological and hence, as expected, is similar both during and outside the crisis. In Column 5, we examine the effect of weather shocks on yields over the entire sample and again do not find any significant differential effects over time. One potential concern in the interpretation of our results below is that farmers are able to hedge weather shocks by purchasing crop insurance. However, the development of crop insurance markets implies that this is of limited concern in our setting. While crop insurance markets have been available since the 1930s, they operated on a limited basis until the 1990s, when the United States government passed a number of laws that greatly expanded the insurance market through subsidies and reinsurance by the government in response to the debt crisis of the 1980s. This fact notwithstanding, the presence of hedging would bias our effects *downward*, as insurance would make farm net worth less sensitive to the effect of weather shocks.

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. 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. This is because such shocks will reduce the amount of cash and net worth of local buyers—

i.e. nearby farmers—who will thus have less funds to purchase land.[18] This is a cash-in-the-market pricing effect as in Shleifer and Vishny, 1992, and Allen and Gale, 1994.

As in all models of liquidity 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. This assumption is likely satisfied in the market for agricultural land, which is generally thought to be highly localized. Still, 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.[19] For each of the 1,971 sales of agricultural land in Hamilton, we mark the county of the buyer in the transaction. As can be seen in Figure 6, the data confirm that agricultural land sales are highly localized: the mean percent of out-of-county buyers is only 9.4%. Interestingly, the fraction of out of county buyers increases substantially during the financial crisis, reaching 25% 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, whereby non-local capital flows into the market to buy underpriced assets.

Having confirmed that agricultural land markets are localized, we examine the effect of exogenous county-level 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 liquidity-pricing prediction, Table 3 shows that land prices do indeed respond negatively to detrimental weather-driven cash flow shocks. Focusing on Column (2), which includes county fixed effects and hence is identified off of temperature variation within a county, an additional day during the growing season with an average temperature greater than 83 degrees Fahrenheit reduces average price per acre by 0.4 of a percent. In Column 3, which reports the results for the period during the peak of the

[18] To reiterate, a reduction in the variable *Days Above 83* captures exogenous positive cash flow injections into a county.
[19] The data are hand-collected from the Hamilton county courthouse where they are located in non-electronic form.

farm debt crisis, the estimated magnitudes are even larger (0.7 of a percent per day with temperature exceeding 83 Fahrenheit).

To provide intuition as to why land prices move following a negative weather shock, it is instructive to conduct a back-of-the-envelope estimate of the effect of weather variation on farm balance sheets. First note that farming involves low profit margins—on the order of 6%.[20] Consider then a shock that adds an extra high temperature day to the growing season—i.e. with average temperature above 83 degrees Fahrenheit—which as discussed above, reduces average annual yield by 3.3%. Assuming conservatively that costs are unaffected by the bad weather shock, annual profits are expected to decline by approximately 50%.[21] Because of small profit margins, variation in weather can thus have a large influence on farm cash positions—a standard operating leverage effect—which then feeds into land prices as shown in Table 3.

Table 3 focuses on the farm debt crisis period, and shows that weather variation and the attendant cash flow effects have an impact on land prices. At the center of the theoretical argument is the assumption that financial frictions prevent firms from raising external financing to smooth shocks, or make it prohibitively costly for them to do so. According to this argument, we 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, and the implied impact on firm balance sheets, *outside* of the 1980s Farm Debt Crisis. In contrast to the results in earlier columns, and consistent with an increased ability of firms to smooth cash flow shocks, outside of the crisis years weather variation has no statistically significant relationship with asset prices. Thus, even though negative weather shocks continue to detrimentally affect yields outside of the crisis

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

[21] With a 6% profit margin, $P = 0.06 \times R$ and $C = 0.94 \times R$, where P, R, and C are profit, revenue, and cost, respectively. Since the weather shock reduces revenue by 3.3%, the resultant profit—i.e. post-weather shock—will be 0.027R rather than 0.06R. Profit thus declines by approximately fifty percent.

(Table 2, Column 4), they have no effect on land values outside the crisis.[22]

Tables 2 and 3 provide a reduced form estimation of the relation between weather shocks and both yields as well as land values. To understand the economic impact of how variation in yields affects land values, we employ an instrumental variable approach. The first stage instruments for yields using exogenous weather shocks, as in regression (1). The second stage then relates county average land value 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, as before, $\log\left(\widehat{Yield_{i,t}}\right)$ is instrumented log corn yield estimated via (1) in county i in year t, and $Land\ Value_{i,t}$ is the land value of county i in year t. In the above, δ_t, represents a vector of year fixed effects, and η_t represents a vector of county fixed effects.

The results are shown in Table 4. Column (1) of the table provides the first-stage estimation. As can be seen, the F-test is 12.79, well above 10, showing that there is little concern of a weak instruments problem. Column (2) of the table exhibits the results of the second stage, finding an elasticity of land values to yields of 0.114: a 10% increase in county yields is associated with a 1.14% increase in land values. Exogenous (weather-driven) cash flow injections are thus found to affect asset prices during the debt crisis. Columns (3) and (4) conduct the IV strategy starting from 1984—the height of the crisis years—and up to its end in 1987. While the first-stage effect relating weather shocks to yields is attenuated, the second stage elasticity of land prices to yields is 0.33, or roughly three times larger than the effect during the entire crisis period.[23]

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[22] 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. Such shifts in beliefs regarding fundamental value could explain the decline in land values following negative weather shocks, this through a classic channel asset-pricing channel, completely orthogonal to any impact stemming from the strength of buyer balance sheets. However, this expectation-driven explanation is not consistent with the fact that land values exhibit no relation with weather shocks outside of the crisis.

[23] This is potentially indicative of higher financial constraints during the height of the crisis.

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 in cash flow propagated into the financial sector during the debt crisis. In the presence of financial frictions, temporary negative weather shocks will reduce farms' ability to repay loans. If this effect is sufficiently severe, cash flow shocks will transmit into the financial sector with increased bank failure rates. Cash injections and the strength of firm balance sheets in the real sector can therefore impact and spill over into the financial sector.

To analyze this mechanism, we first verify that negative 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 above, we use an IV approach in which we run a first-stage regression where county average corn yields are instrumented with *Days Above 83*, the weather shock variable.[24] The second stage then relates county-level aggregate balance of delinquent loans to county average yields. 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 estimated via (1) in county i in year t, and *Ag Delinquencies* is the total outstanding balance of delinquent agricultural loans.

Column (1) of Table 5A presents the results. As can be seen, delinquency levels vary negatively with yields. Indeed, the coefficient implies an elasticity of 3 between county aggregate delinquent loans and average yields. During the crisis, counties which experience a 10% increase in yields (as compared to their mean) exhibit a 30% increase in aggregate delinquency amounts. Thus,

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

as one would predict, during the debt crisis positive cash injections driven by weather shocks translated into reduced delinquencies among borrowers.

The loan delinquencies analyzed in Column (1) of Table 5A represent, of course, shocks to bank balance sheets. As a next step, then, we examine whether the increased loan delinquencies driven by (weather-induced) variation in cash flows were transmitted into the local financial sector in the form of county bank failures. We employ our standard IV 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 IV 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 year t, and zero otherwise. Note that we measure bank failures in the period that follows the growing season in year t up to the end of the growing season next year.

Column (2) of Table 5A presents the results. As the table shows, a 10% increase 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. 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 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 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—i.e. during the years 1988 to 2010.[25] 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 delinquency rates or bank failure rates.

3.4 Cash Flow Shocks and Labor Markets: Employment and Wages

We continue by analyzing the effect of temporary 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 cash variation and labor markets outcomes within the agricultural sector. We collect county average pay and county employment levels from the quarterly census of employment and wages. All regressions employ the IV approach, whereby county average yields are instruments 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 estimated via (1) in county i in year t. For the labor-market outcomes, *Ag Total Wages* is the sum total of all wages for agricultural crop production, *Ag Avg Wages* is the average annual wage for an individual in agricultural crop production, and *Ag Employment* is the total employment in agricultural crop production.

Column (1) of the table shows the results using total county-level employment as the dependent variable.[26] As can be seen, there is a positive relation between yields and total county employment. Thus, during the crisis, farms in counties that received a positive cash flow injection

[25] There were 8 failures during this period, though 7 of them took place in 1988 and 1989.
[26] Note that the data from QCEW does not have information for small farms, thus one could expect the true magnitudes to be larger as small farms tend to be more financially constrained.

(driven by relatively good weather) reduced by less their total agriculture employment relative to 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) 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. The elasticity of yields to average county pay is approximately 2.9. Thus, consistent with a drop in labor demand stemming from an inability to finance employee wages out of internal capital, a 1% reduction in yields is associated with a substantial 3% relative reduction in average wage per employee. Column (3) combines the results in Columns (1) and (2) by analyzing total county wages, which includes variation both in employment as well as average wage per employee. Unsurprisingly, given the results in the prior columns, we find that weather driven cash flow injections are positively related to total county wages, with a total wages to yield elasticity of 4.4.

Panel B of the table 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. 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.

Table 7 continues by analyzing how cash flow shocks spill over into other labor markets during the debt crisis. Specifically, we use the IV strategy from above, instrumenting for county yields, and then relate predicted yields to county level employment and wages in the *service* sector. We focus our attention on the service sector as local demand effects should be concentrated there, as well as because it is a natural place for employees dislocated from farming to seek employment.[27]

Column (1) of Table 7A shows that total employment in the service sector is *negatively* related to cash flow shocks in the agricultural sector. Thus, 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). Following a temporary negative cash flow shock, workers thus appear to be shifting from the adversely affected agricultural sector towards other industries. The coefficient on the employment variable shows that a 1% reduction in predicted yields is associated with an increase of 7 employees in the service sector. Note that the number estimated here is greater than the reduction in employees in the agricultural sector. This is driven by the fact that employment data from QCEW for the agricultural sector only tracks large agricultural operations and hence does not incorporate changes in small farms. Visual inspection of overall employment in Iowa also confirms that there was little change in the overall employment rate over the period of the farm debt crisis (see Figure 7).

Still focusing on the debt crisis period, Column (2) of the table 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 results show 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 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 yields translates into a 1% drop in

[27] We also examined manufacturing sector and found no significant adjustments in employment in manufacturing. Data is taken from QCEW as discussed earlier.

service sector wage.

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

The final column of Table 7A examines the relation between predicted yields—instrumented as usual by the weather shock variable—and the number of service sector establishments within each county. As can be seen, there is a negative relation between the two variables: during the financial crisis, negative cash flow shocks to the agriculture sector are associated with an increase in the number of new establishments in the service sector. This is consistent once again with spillovers between sectors in which employees are shifting away from agriculture and opening new establishments in the service sector.

The results in Panel A of Table 7 thus paint a picture by which 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 farms are able to smooth weather shocks, consistent with the greater availability of external finance outside of the crisis. 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 IV 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.

Table 6 shows 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. This suggests a second channel—related to shifts in demand—through which cash flow shocks during a financial crisis can spillover into other sectors. According to this, once a given sector is hit by a cash flow shock, firms in the sector cut employment, causing dislocated employees to reduce 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.[28]

To test this mechanism, we run similar regressions to those in Table 7 relating employment and wages in services to weather-induced cash flow shocks in agriculture, but interact the cash flow shocks with the importance of agriculture in each county. The county-level importance of agriculture is measured by the percentage of total county income that is comprised of farm crop income, while weather shocks are measured as before using the number of growing season days with average temperature above 83 degrees Fahrenheit. We predict that in counties with a dominant agriculture sector, 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 in the results of Table 7, 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.

[28] 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.

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 agriculture *reduce* employment in services. During a debt-crisis—when firms likely cannot easily smooth temporary shocks by raising external finance—aggregate county-level cash flow shocks in one sector impose negative employment externalities on other sectors operating within the same geography.

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 using the IV 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 IV specifications for below median and above median farm importance counties.[29] The results are broadly 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, as can be seen from Columns 3 and 4 of Table 8B, wages are positively related to predicted yields, although the effect is not statistically

[29] The median ratio of farm income to total county income is .213.

significant in above-median farming importance counties.

3.5 Cash Flow Shocks and Income Per Capita: The Income Multiplier During the 1980s Debt Crisis

The results of the prior sections show how county-level cash flow shocks during the debt crisis had a sizeable affect 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 temporary cash flow shocks ultimately translate into an impact on county-level income. 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 Panel A of Table 9. As can be seen, during the farm debt crisis, instrumented yields are positively related to income per capita, with an elasticity of 0.13. In contrast, the point coefficient on predicted yields outside of the farm debt crisis period is approximately one third smaller and not statistically significant.

It is instructive to use the results in Table 9A to conduct a back-of-the-envelope calculation of the multiplier effect of county level cash-flow shocks on county income per capita. Based on the elasticity of 0.13 in Table 9A, a 10% weather-driven drop in yields during the crisis is associated with a 1.38% drop in county income per capita. A 1.38% drop in income per capita from its average level during the crisis of $25,855 (in 2010 real dollars) is equivalent to $356.80 per capita. On the other hand, the 10% drop in yields is equivalent to a reduction of $219.55 in county per capita corn sales.[30] Thus, our results indicate that during the debt crisis, the multiplier between the exogenous county

[30] To see this, note that the average yield during the crisis was 123.8 bushels per acre while the average real price of corn was $4.10 per bushel. The 10% drop in yields is this equivalent to a 12.38 × 4.10 = $50.76 drop in sales per acre. The average acreage of grown corn per county was 122,854 while the average county population was 28,402. This implies that a 10% drop in yields was associated with a $219.55 (= $50.76 × 122,854 / 28,402) drop in county per capita sales.

level cash flow shock and county-level income is \$356.80/\$219.55 = 1.63. Thus, based on these estimates, cash flow injections had a significant impact on local economic income during the crisis.[31]

Panel B of Table 9 runs the reduced form regression, relating directly the weather shock variable *Days Above 83* to the log of county income per capita (i.e. without instrumenting for county yields). As can be seen, during the crisis, negative weather shocks reduce county-level income, with the effect persistent up to a year following the crisis. Two-year lagged weather-driven cash flow shocks do not exhibit a statistically significant relation with county-level income.

As a consistency check, Table 9B can also be used to calculate the county level income-to-cash-flow shock multiplier. Based on Column (1) of Table 9B, an additional growing season day with temperature above 83F 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 83F leads to a 2.2% 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.[32] 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.

Panel C of Table 9 reruns the reduced form specification relating the *Days above 83* variable to the log of county income per capita, but adds an interaction term between the weather shock variable and farm importance (as measured by the lagged percentage of total county income that is comprised of farm crop income). Similar to the interaction results in Section 3.4 analyzing labor markets, we expect the multiplier between weather-driven cash flow shocks and income-per-capita

[31] As Panel 9A shows, outside of the debt crisis, the point estimate of the income-per-capita to yield elasticity is 0.34 with a 95% confidence interval of -0.26 to 0.94.

[32] 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% drop in corn yields leads to a drop of $\$4.1 \times 123.8 \times 0.022 = \$11.17$ 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 $\$11.17 \times 122{,}854 \,/\, 28{,}402 = \$48.30$.

to be larger in counties where farming plays a larger role.[33] This is precisely what the results indicate: the coefficient on the interaction between weather shocks and farm importance is negative and statistically significant. Cash flow to income-per-capita multipliers were higher during the debt crisis in counties with greater farm importance. Following a calculation along the lines described above, during the debt crisis, the multiplier for counties in the 25th percentile of farm importance (farm income percentage equals 0.125) exhibit a multiplier of 1.2. In contrast, the multiplier for counties in the 75th percentile of farm importance (farm income percentage equals 0.31) exhibit a multiplier of 2.21.

4 Conclusion

In this paper, we examine the general equilibrium effects of variation in firm cash flows during a financial crisis, and how these affect the propagation of shocks. In order to do so, we construct a novel database in the agricultural industry encompassing the 1980s farm debt crisis. Using weather shocks as a source of exogenous cash flow variation, we examine the relation between cash flow shocks during the crisis and a host of general equilibrium outcomes in the real and financial sector.

We find that temporary cash flow shocks during the crisis have significant effect on farmland values, delinquencies, and employment and wages in the agricultural sector. Beyond the direct effects in the farming sector, we also find that these shocks spillover to other sectors. We find that the likelihood of failure of banks increases in counties that experience a negative cash flow shock. Furthermore, we find that the services sector picks up the workers displaced from farming, but that the average wage of employees in services drops by more in counties where there is a

[33] This is equivalent to the hypothesis that cash-flow to income multipliers during debt crisis are convex in the level of the cash flow injection.

negative cash flow shock. Overall, temporary shocks that affect firm balance sheets during a crisis create externalities for other sectors.

Our results highlight the potential importance of cash injections to firms during a financial crisis. The results also underscore how injections in one sector can spillover to other sectors of the economy. More broadly the results highlight the adjustments that occur in the economy in equilibrium during a financial crisis, when firms experience shocks that affect the strength of their balance sheet.

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Table 1: Summary Statistics

This table contains summary statistics for all variables, split between the crisis and non-crisis years. All variables are yearly county-level averages. *Corn Yield* is defined as bushels of corn produced per acre of harvested land. *Land Value* is the dollar value of farmland per acre, in real (2010) dollars. *Days Above 83* is the number of days where the average temperature is above 83 degrees Fahrenheit during the growing season. Statistics for the non-crisis period are presented from 1950-1980 and from 1988-2010; statistics for the crisis period are presented from 1984 to 1987. All dollar amounts are scaled by the consumer price index (CPI), and are in real 2010 dollars.

Panel A: Crisis Years

Variable	# Obs	Mean	Std. Dev.	p25	Median	p75
Days Above 83	396	2.377	3.070	0.285	1.222	3.054
Corn Yield	396	123.827	15.214	115.15	125.75	134.30
Land Value	396	1,977.861	751.778	1,488.387	1,868.923	2,299.06

Panel B: Non-Crisis Years

Variable	# Obs	Mean	Std. Dev.	p25	Median	p75
Days Above 83	5,339	2.512	3.642	0.047	1.069	3.216
Corn Yield	5,346	105.671	41.483	71.100	100.700	139.100
Land Value	5,346	2,753.98	1,361.00	1,893.49	2,424.75	3,127.98

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. *Days Above 83* is the number of days where the average temperature is above 83 degrees Fahrenheit during the growing season. *Crisis* is a dummy variable that equals 1 if the year is between 1981 and 1987, and 0 otherwise. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). 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)	(5)
Time Period:	Crisis, 1981-1987		Crisis, 1984-1987	Non-crisis	Full Sample
Days Above 83	-0.034***	-0.033***	-0.022***	-0.026***	-0.026***
	(0.008)	(0.008)	(0.004)	(0.003)	(0.003)
Days Above 83					-0.005
× *Crisis*					(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Standard Errors	Spatial	Spatial	Spatial	Spatial	Spatial
Observations	693	693	396	5,339	6,032
R^2	0.660	0.800	0.754	0.925	0.919

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. *Days Above 83* is the number of days where the average temperature is above 83 degrees Fahrenheit during the growing season. *Crisis* is a dummy variable that equals 1 if the year is between 1981 and 1987, and 0 otherwise. Standard errors are given in parentheses, and are corrected for spatial correlation (as in Conley, 2008), as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). 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)	(5)
Time Period:	Crisis, 1981-1987		Crisis, 1984-1987	Non-crisis	Full Sample
Days Above 83	-0.031***	-0.004***	-0.007***	-0.001	-0.0005
	(0.008)	(0.001)	(0.002)	(0.001)	(0.001)
Days Above 83					-0.005***
× *Crisis*					(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Standard Errors	Spatial	Spatial	Spatial	Spatial	Spatial
Observations	693	693	396	5,339	6,032
R^2	0.709	0.996	0.994	0.982	0.983

Table 4: Temperature Shocks, IV Regressions during the Crisis

This table provides instrumental variables 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. *Days Above 83* is the number of days where the average temperature is above 83 degrees Fahrenheit 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%, 5%, and 1% 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
Dep. Variable:	log(*Corn Yield*)	log(*Land Value*)	log(*Corn Yield*)	log(*Land Value*)
Days Above 83	-0.033***		-0.022***	
	(0.004)		(0.002)	
$\widehat{\log(Yield)}$		0.114***		0.330***
		(0.031)		(0.057)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	693	693	396	396
F-stat	12.79		9.18	
R^2		0.996		0.99

Table 5: Agricultural Loan Delinquencies and Bank Failures

This table provides second-stage instrumental variables 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. *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. *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. $\widehat{\log(Yield)}$ is instrumented log corn yield. Standard errors are given in parentheses, and are clustered at the year level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). The crisis period in Panel A runs from 1984 to 1987, while the Non-Crisis period in Panel B runs from 1988-2000 for column (1) and from 1988-2010 for column (2).

Panel A: Crisis

	(1)	(2)	(3)
Dep. Variable:	log(*Ag Delinquencies*)	*Bank Failure*	*Bank Failure Crisis*
$\widehat{\log(Yield)}$	-3.249***	-0.324**	-0.402***
	(0.836)	(0.144)	(0.064)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	396	396	396
R^2	0.504	0.239	0.740

Panel B: Non-Crisis

	(1)	(2)
Dep. Variable:	log(*Ag Delinquencies*)	*Bank Failure*
$\widehat{\log(Yield)}$	-0.707	0.065
	(1.276)	(0.044)
Year FE	Yes	Yes
County FE	Yes	Yes
Observations	1,273	2,270
R^2	0.375	0.068

Table 6: Agricultural Wages and Employment

This table provides second-stage instrumental variables 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 Total Wages* is the sum total of all wages for agricultural crop production. *Ag Avg Wage* is the average annual wage for an individual in agricultural crop production. *Ag Employment* is the total employment in agricultural crop production. $\log(\widehat{Yield})$ 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%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). The crisis period in Panel A runs from 1984 to 1987, while the Non-crisis period in Panel B runs from 1975-1980 and from 1988-2000.

Panel A: Crisis

	(1)	(2)	(3)
Sector:	Agricultural Crop Production		
Dep. Variable:	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)
$\log(\widehat{Yield})$	29.955**	2.866**	4.368**
	(14.725)	(1.360)	(2.005)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	396	396	396
R^2	0.662	0.748	0.740

Panel B: Non-Crisis

	(1)	(2)	(3)
Sector:	Agricultural Crop Production		
Dep. Variable:	*Ag Employment*	log(*Ag Avg Wage*)	log(*Ag Total Wages*)
$\log(\widehat{Yield})$	-6.386	1.130	1.419
	(7.147)	(0.918)	(1.175)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	1,875	1,875	1,875
R^2	0.370	0.436	0.454

Table 7: Wages and Employment in the Services Sector

This table provides second-stage instrumental variables 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 Total Wages* is the sum total of all wages for the services sector. *Services Avg Wage* is the average annual wage for an individual in the services sector. *Services Employ* is the total employment in the services sector. *Services Estabs* is the number of establishments in the services sector. $\widehat{\log(Yield)}$ 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%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported). The crisis period in Panel A runs from 1984 to 1987, while the Non-crisis period in Panel B runs from 1975-1980 and from 1988-2000.

Panel A: Crisis

	(1)	(2)	(3)	(4)
Sector:	Services Sector			
Dep. Variable:	*Services Employ*	log(*Services Avg Wage*)	log(*Services Total Wages*)	*Services Estabs*
$\widehat{\log(Yield)}$	-720.705***	0.075**	-0.002	-41.349***
	(106.572)	(0.033)	(0.045)	(8.079)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R^2	0.997	0.970	0.998	0.999

Panel B: Non-Crisis

	(1)	(2)	(3)	(4)
Sector:	Services Sector			
Dep. Variable:	*Services Employ*	log(*Services Avg Wage*)	log(*Services Total Wages*)	*Services Estabs*
$\widehat{\log(Yield)}$	-158.728	0.074	0.063	-1.727
	(715.692)	(0.098)	(0.159)	(45.914)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	1,875	1,875	1,875	1,875
R^2	0.916	0.317	0.868	0.999

Table 8: Services Employment and Dependence on Farm Income

This table provides regression results for the effects of temperature shocks on services 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 IV specifications for each (second-stage results are provided). All variables represent county-level values in the indicated year. *Services Employ* is the total employment in the services sector. *Services Avg Wage* is the average annual wage for an individual in the services sector. log(*Income*) is log income per capita (in real 2010 dollars). *Days Above 83* is the number of days where the average temperature is above 83 degrees Fahrenheit 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. All regression 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%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported).

Panel A: Interaction	(1)	(2)
Dependent Var:	*Services Employ*	log(*Services Avg Wage*)
$(Days\ Above\ 83)_t$	55.913***	-0.003***
	(21.592)	(0.0002)
$(Days\ Above\ 83)_t$	-234.717***	0.008
× *Farm Income Pct*	(81.837)	(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: IV Regressions

	(1)	(2)	(3)	(4)
	Below-Median Income Dependence		Above-Median Income Dependence	
Dependent Var:	*Services Employ*	log(*Services Avg Wage*)	*Services Employ*	log(*Services Avg Wage*)
$\log\widehat{(Yield)}$	-679.249***	0.085**	40.615***	0.091
	(243.431)	(0.036)	(12.205)	(0.085)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	176	176	220	220
R^2	0.997	0.976	0.992	0.917

Table 9: Temperature Shocks and County Income

This table provides regression results for the effects of temperature shocks on county income per capita. Panel A gives instrumental variables results for county income, while Panel B explores persistence. All variables represent county-level values in the indicated year. log(*Income*) is log income per capita (in real 2010 dollars). *Days Above 83* is the number of days where the average temperature is above 83 degrees Fahrenheit during the growing season. $\widehat{\log(Yield)}$ is instrumented log corn yield. The non-crisis period includes 1959, 1969-1980, and 1988-2010. Standard errors are given in parentheses, and are clustered at the year level in Panel A, and are corrected for spatial correlation (as in Conley, 2008) in Panel B. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All regressions include an intercept term (not reported).

Panel A: Temperature Shocks and County Income

Dependent Variable: log(*Income*)

	(1)	(2)
Time Period:	Crisis, 1984-1987	Non-crisis
$\widehat{\log(Yield)}$	0.138***	0.034
	(0.051)	(0.031)
Year FE	Yes	Yes
County FE	Yes	Yes
Observations	396	3,557
R^2	0.948	0.952

Panel B: Temperature Shocks and Persistence, County Income

Dependent Variable: log(*Income*)

	(1)	(2)	(3)	(2)
Time Period:	Crisis, 1984-1987			Non-crisis
$(Days\ Above\ 83)_t$	-0.003***	-0.003***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$(Days\ Above\ 83)_{t-1}$		-0.002*	-0.002**	0.001
		(0.001)	(0.001)	(0.001)
$(Days\ Above\ 83)_{t-2}$			-0.0001	0.0002
			(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Standard Errors	Spatial	Spatial	Spatial	Spatial
Observations	396	396	396	3,543
R^2	0.939	0.942	0.942	0.950

Figure 1: Response of Corn Yields to Temperature

This figure, taken from Schlenker and Roberts (2006), shows the response of corn yield to temperature during the growing season. The curve represents the impact of one day of exposure of the indicated temperature on yearly log yields, relative to a temperature of 8˚C.

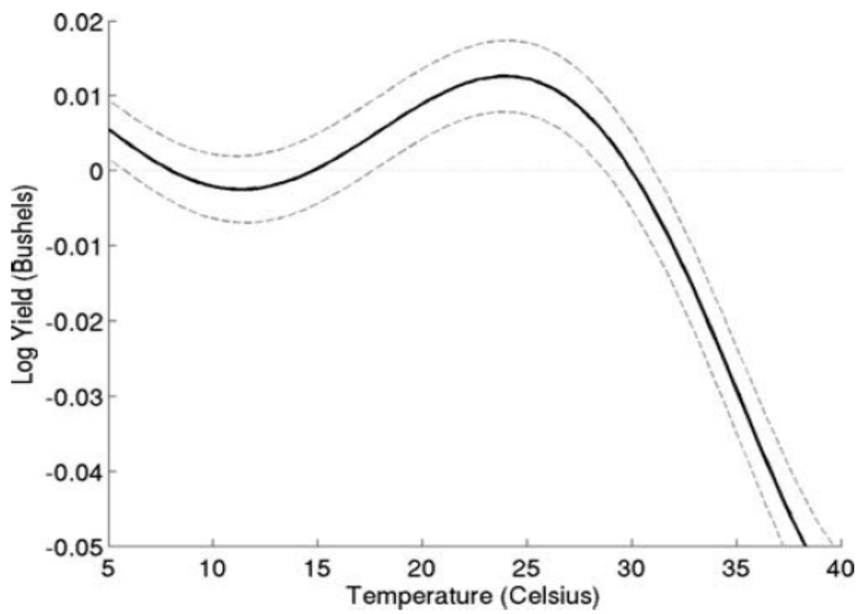

Figure 2: Distribution of Temperature Shocks

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 degrees Fahrenheit.

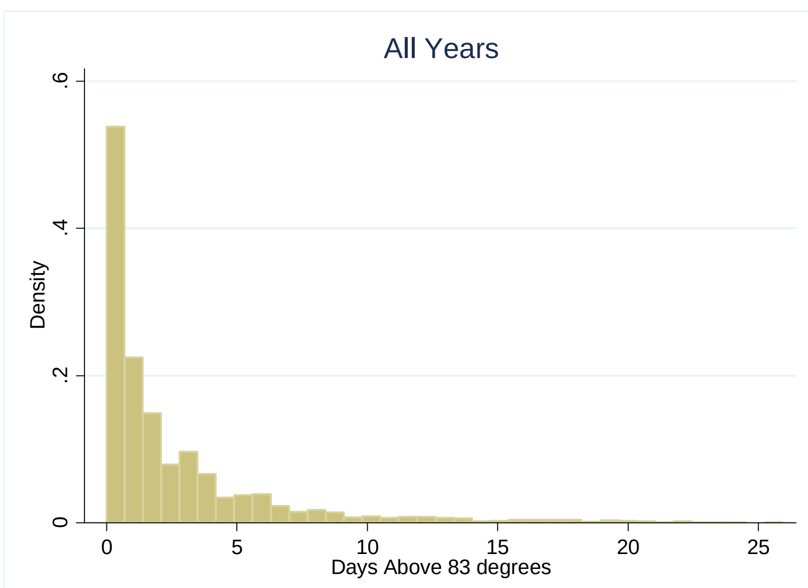

Figure 3: Distribution of Temperature Shocks in Excess of Averages

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 degrees Fahrenheit.

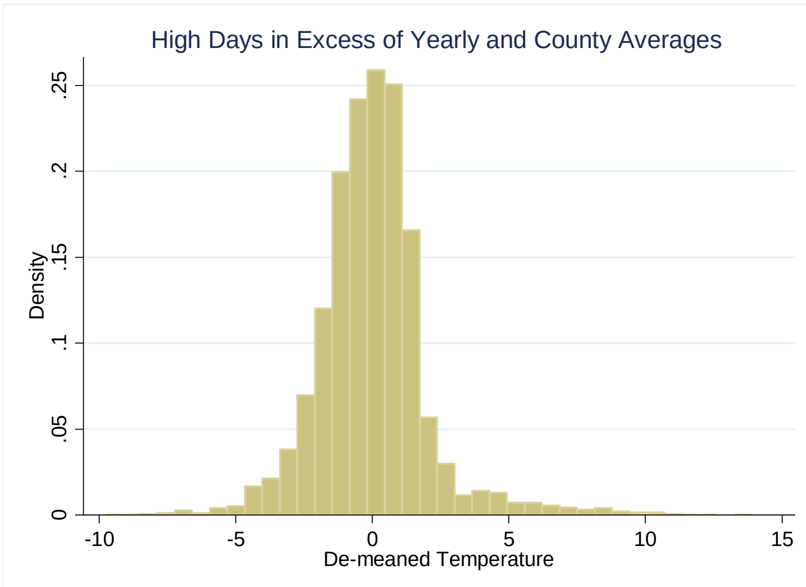

Figure 4: Distribution of Temperature Shocks in Different Years

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 degrees Fahrenheit.

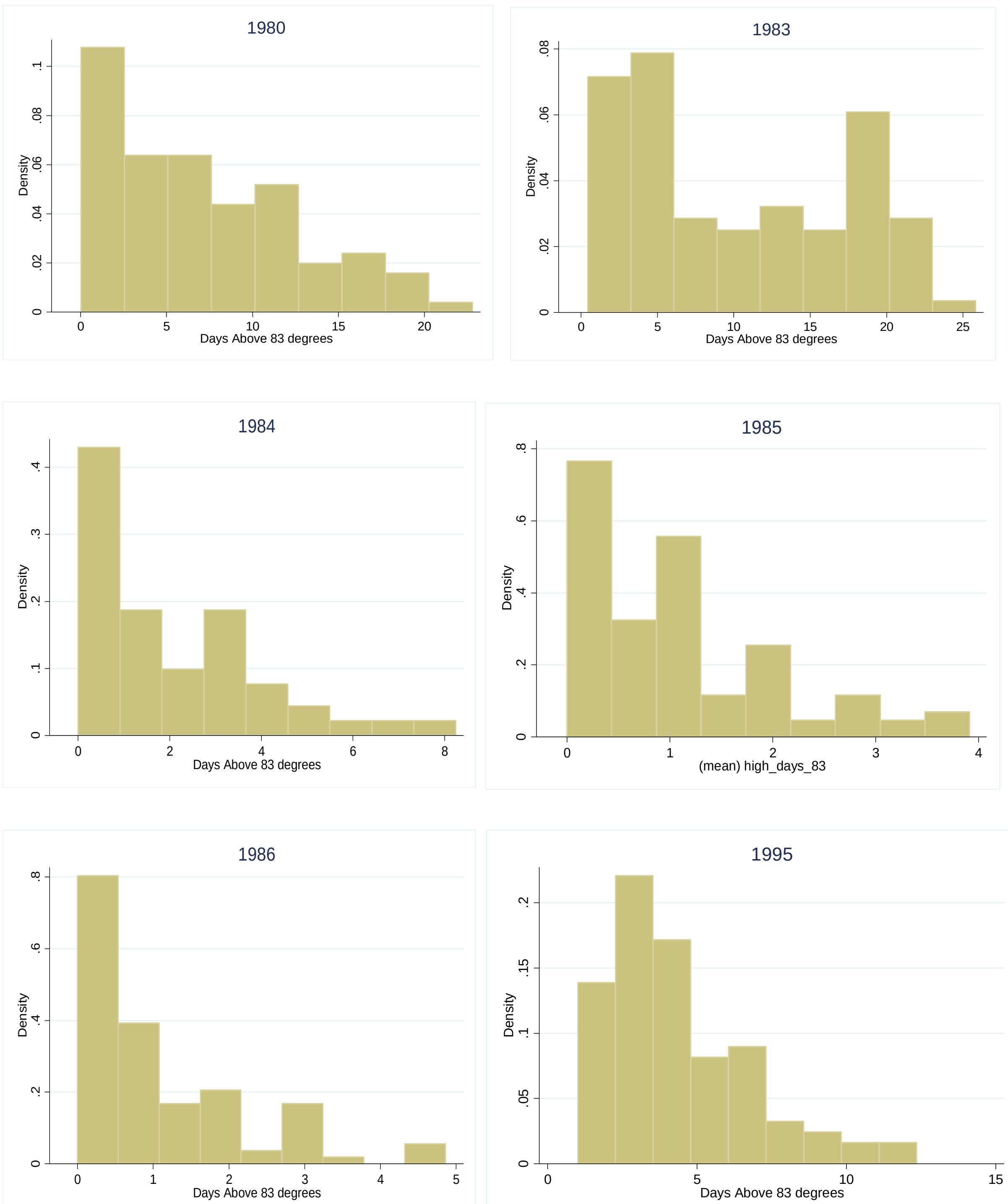

Figure 5: Corn Yields, Farm Land Values, and Agricultural Debt over Time

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.

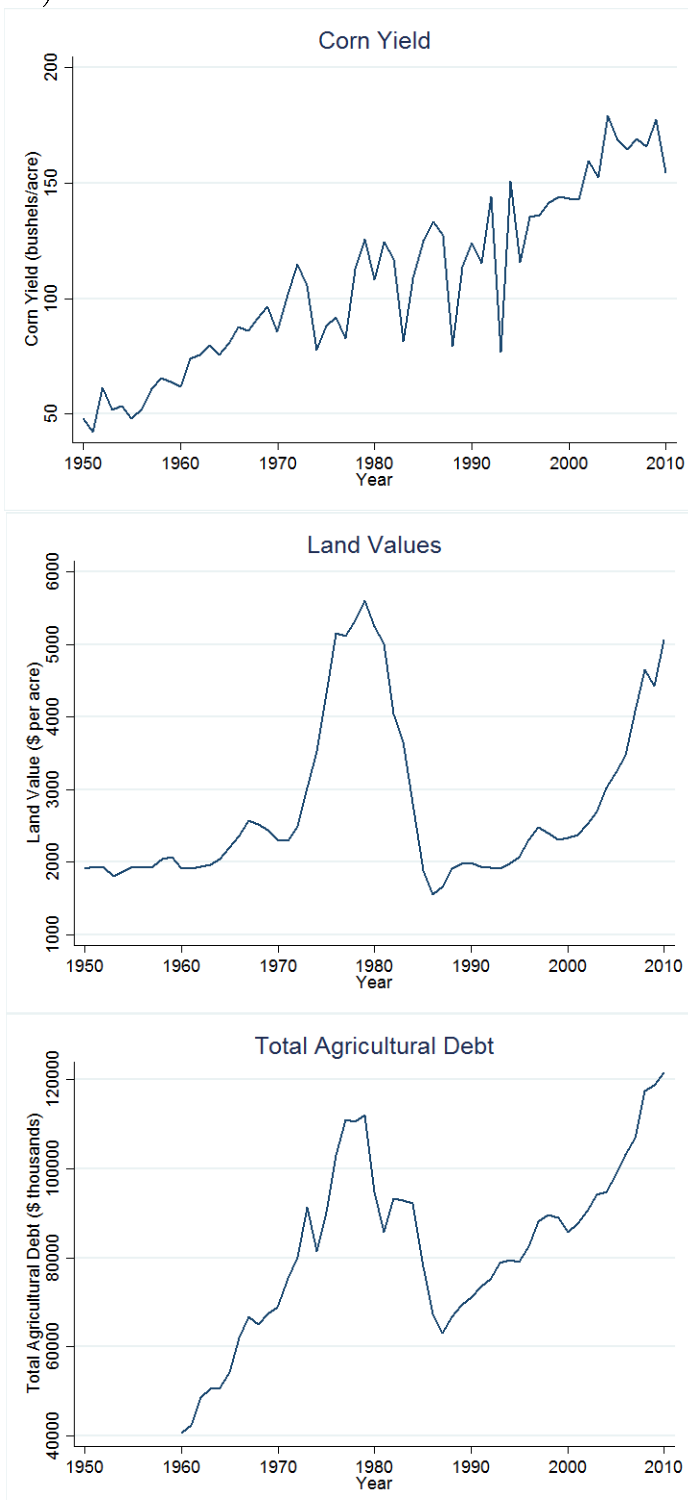

Figure 6: Land Purchases in Hamilton County

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.

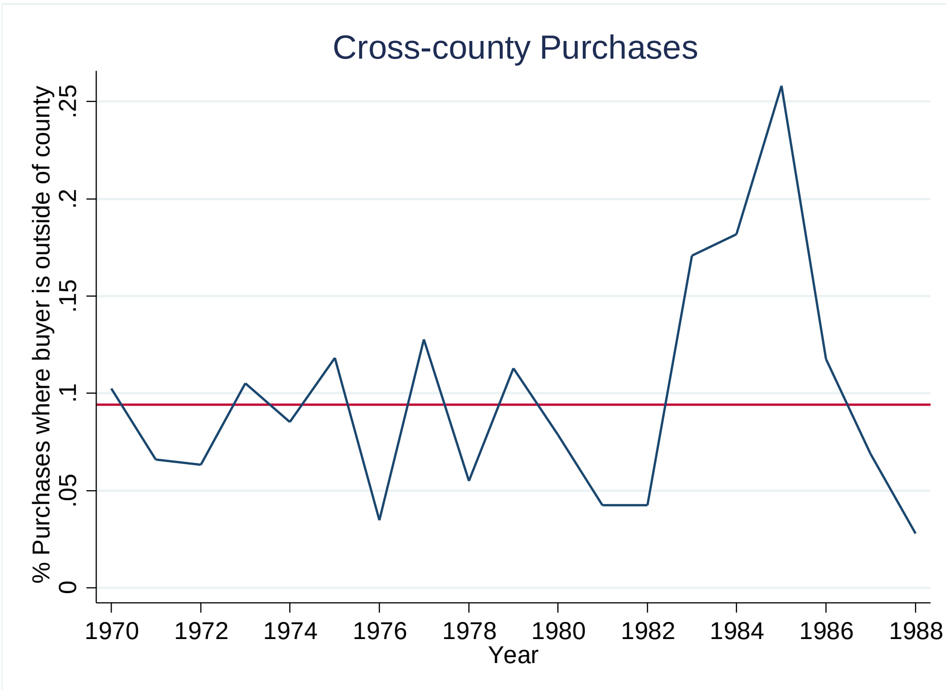

Figure 7: Employment and Wages

This figure gives total employment and total wages over time for the agricultural crop sector (top graph) and all sectors (bottom graph). Each data point represents the sum of employment or wages across all counties in Iowa. Wage numbers are in millions of real (2010) dollars.