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Abstract

We study how the availability of credit shapes adaptation to a climatic shock, specifically, the long 1950s US drought. We find that bank lending, net immigration, and population growth decline sharply in drought exposed areas with limited initial access to bank finance. In contrast, agricultural investment and long-run productivity increase more in drought-exposed areas when they have access to bank finance, even allowing some of these areas to leapfrog otherwise similar areas in the subsequent decades. We also find unequal access to finance can drive migration from drought-hit finance-poor communities to finance-rich communities. These results suggest that broadening access to finance can enable communities to adapt to large adverse climatic shocks and reduce emigration.

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As mitigation efforts lag, the world heats up, and climate volatility increases, the issue of climate adaptation becomes important. What factors can help a population adapt to adverse climate shocks? Can these factors affect long range outcomes? To answer these questions, we examine the consequences of a drought that was both long and affected significant areas of the United States in the 1950s. The 1950s drought was the second most severe drought to affect the US at the time (after the "Dustbowl" during the Great Depression), and for many states it was the most severe drought on record. Our particular focus is on whether access to bank finance helped to shape long run adjustment to the drought, and the specific channels through which adjustment occurred. We use newly collected banking data to help measure credit constraints at a relatively high spatial resolution. The analysis combines these data with information on demographics, agricultural investment, and technology adoption over the subsequent decades.

We find that the profound and long-lasting demographic shifts associated with large climate shocks are mediated by access to bank finance. For a county at the 10th percentile of the log of per capita loans in 1950—one measure of ex-ante credit availability—drought exposure is associated with a 6.3 percentage point decline in population growth between 1950-1960 (p-value=0.01). But for a county at the median level of the per capita credit availability, the implied effect of the drought on population growth is only a 1.5 percentage point decline (p-value=0.41). These effects are even larger in the long run. At the 10th percentile of the log of per capita loans in 1950, drought exposure suggests a 10.3 percentage point decline in population growth in the county over the next 30 years (p-value<0.00). Even at the median per capita bank credit availability, drought exposure implies a 4.9 percentage point decline in the 1980 population relative to 1950 (p-value=0.07).

Of course, the extensive literature on finance and growth would suggests there should be some direct effect of credit availability on population growth.[1] However, while the direct effect of finance is modest, the role of finance in mediating the effect of the adverse climate shock is considerable. For two drought exposed towns with identical populations in 1950, the 1980 population is about 4.5 percentage points higher for the town at the median of bank credit availability relative to one that is at the 10th percentile in 1950.

[1] See, for example, King and Levine (1993) and Rajan and Zingales (1998).

Emigration is an important adjustment margin, as populations that are climate-affected but cannot adapt are forced to emigrate (see, for example, Bohra-Mishra, Oppenheimer et al. (2014), Hornbeck (2012, 2022), and Long and Siu (2016)), while immigration and increased fertility suggest success in preserving livelihoods. Our evidence shows that these population shifts reflect both emigration from drought-affected areas with limited credit access, especially by the young, as well as long-run changes in fertility and mortality. In 1960, in a county with low credit availability drought exposure is associated with a decline in the percent of domestic migrants. Much of the net migration is concentrated among the young. The ratio of 20-29 year olds for example declines in drought exposed counties with limited credit access, while the ratio of those over 70 years of age increases in these areas.

Given who stays and who leaves as a result of credit constraints, drought-exposed areas experience long-run demographic decline. With the emigration of the prime working age population, drought exposure is associated with a drop in the number of live births in 1960 for a county with low credit availability. Partly because the population left behind in drought exposed counties with limited credit access is older, the post-drought mortality rate is also higher.

The channel by which our proxy for credit availability matters is obviously of interest. If low levels of credit per capita reflect frictions in lending such as the inadequate capacity of banks to do due diligence, limited trust in potential borrowers or their lack of fungible collateral, or the lack of capital in local banks, then the drought might exacerbate credit supply constraints in low credit-availability areas and shrink lending relative to high credit-availability areas. If, however, a low level of credit per capita simply reflects low demand, then the drought could well magnify lending in low credit per capita areas relative to other areas.

We find that bank lending increased sharply in response to the drought in areas with ex-ante greater credit availability. The time variation in the data also show that this relative surge in lending in drought-exposed areas with greater credit availability reflects a specific credit supply response to drought-related credit demand, as there is no similar pattern in the data in the decade before the drought. In keeping with this supply response, we also document a large shift in the composition of banks' assets towards loans in response to drought-related credit demand.

Clearly, ex ante per capita bank credit can proxy for a variety of other factors that could influence the economic adjustment to an adverse shock. To address these concerns, we use two very different strategies to identify the role of credit availability in shaping the economic adjustment to the drought.

First, we use the plausibly exogenous variation in the town-level potential credit supply stemming from capital regulations for bank entry circa 1910. During the sample period, governments used minimum capital requirements to regulate bank entry. These capital requirements were set at the level of the incorporated town in which the bank was headquartered and based on the population of the town, as recorded in the last decennial census. We show that towns subject to higher entry capital requirements, based on state regulations and the town's 1910 population, had banks that survived better the adverse shocks of the 1920s and 1930s.[2] This survival bias resulted in these towns having more banks and greater credit availability in 1950. The identification strategy uses a control function approach based on the town-level variation in the 1910 capital requirement to estimate the effects of (the exogenous component of) credit availability on adaptation to the drought. The control function approach reaffirms that greater credit availability induces large and persistent differences in long-run outcomes between towns similarly affected by the drought.

Our second approach at identification focuses more directly on the mechanism driving credit availability. We use the fact that most agricultural loans are made to nearby borrowers, as well as the fact that state-borders significantly hampered the transference of borrower-specific information and lender rights across state borders relative to their transference intra-state during the sample period (see, for example, Ramcharan and Rajan (2015)). Bank branching networks did not extend across borders, nor was collateral registration or information readily accessible to potential lenders on the other side of the border. Because of these lending frictions at state borders, it was relatively hard for migrants with existing banking relationships to access credit in a new destination across the state border than within the state border.

So if our proxies for local credit availability indeed proxy for credit, we should find that there is more outmigration from a town with low credit availability when there are nearby in-state towns with high credit availability than when there are nearby out-of-state towns with high credit availability. If however credit availability in 1950 proxies for income, local economic diversification, or some other latent factor than availability of credit, then state borders should be

[2] This evidence is consistent with (Carlson, Correia et al. 2022) which documents that national bank capital requirements in the national banking era also affected bank entry and lending in 1890s.

largely irrelevant in shaping the impact of the drought. We find that high credit availability in nearby in-state towns reduces population growth in towns with low credit availability, but we find no such effect for towns with high credit availability, or if credit availability is high in nearby out-of-state towns.

Thus far, we have focused on the demographic consequences of the drought. We turn to the channels through which communities preserve livelihoods and incomes via financing. The most direct response to a drought is to invest in irrigation (Leonard and Libecap 2019, Cooley and Smith 2022). And center pivot irrigation systems, first patented in 1952, rapidly become a pivotal new technology that allowed farmers to irrigate using groundwater, boosting agricultural production in arid areas across the US beginning in the 1950s.[3] We find that drought exposed counties with access to credit significantly increased irrigated farm acreage during the 1950s.

Our sample period was one of broad technological change, and decadal data may conflate the effects of finance with these secular technological shifts. We therefore use high frequency data on about 106,000 water wells between 1950 and 1970 across the US to connect directly drought exposure, credit access and the shift towards ground water irrigation-based agriculture. On average, each well measures the depth of the underlying aquifer—the source of ground-water irrigation-based agriculture—every 80 days. Consistent with the decadal census data showing that access to finance helped facilitate the shift to ground-water based irrigation, we find that aquifer discharge increased sharply in drought exposed areas with access to finance relative to drought exposed areas with aquifers but less access to finance. But within one year after normal rainfall returned, these differences in aquifer discharge vanish, connecting directly access to finance, the timing of the drought, and adaptation through ground-water mining.

There is also evidence that credit availability helped finance a shift to more drought tolerant crops in drought affected counties. Sorghum is one such well-known drought resistant grain and in the 1950s drought years, sorghum production across the US expanded significantly, rising from 12 to 27 million planted acres between 1952 and 1957 (Abdel-Ghany, Ullah et al. 2020). We find that among drought exposed counties sorghum production expanded significantly more in counties with high credit availability.

[3] In drought affected Nebraska, the number of such systems increased from about a dozen in 1952 to around 10,000 by 1954--https://www.smithsonianmag.com/innovation/how-center-pivot-irrigation-brought-dust-bowl-back-to-life-180970243/--accessed on 7/26/2022 and Opie, Miller and Archer (2018).

The 1950s was also a period of rapid increases in farm mechanization, as tractors, combines and heavy trucks incorporated new technologies developed during WWII, helping drought-affected farms become more efficient. We find that mechanization, especially among farms with lower revenues, was significantly higher in counties with greater access to credit. Indeed, it was particularly high when farms could also invest in irrigation, suggesting there were complementarities between the investments that were facilitated by access to credit.

Technological adaptation can both help the agricultural economy better survive the drought but also shape the pattern of production and ownership. For instance, easier credit access can allow marginal farms to survive. In keeping with this hypothesis, we find that tenant farming, which is most fragile because of the lack of land collateral among tenant farmers, fell significantly in drought-hit areas with low credit availability relative to those with high credit availability.

The impact of new technologies and production methods on productivity often takes time to manifest (David 1990). And these differences in investment and the pattern of production and ownership in response to the drought eventually induced large long-run differences in farm productivity and income. The mean value of farm land per farm in 1978 is about 6.45 percent lower among drought exposed counties at the 10th percentile of the ex-ante credit distribution (p-value=0.08), while at the 90th percentile of credit distribution, the marginal impact is positive (5.2 percent). There is also suggestive evidence of leapfrogging. Long-run farm productivity becomes highest among drought exposed farms with both access to credit and the physical means to adapt through ground water irrigation, even exceeding that in non-drought exposed areas.

These effects can also spillover onto the local economy. More productive farmers and higher local incomes on account of better adaptation to the shock can support local demand, preserving the non-tradeables sector relative to counties where demand collapsed amid demographic decline and limited adaptation. The number of retail establishments declines significantly in drought-hit counties with low credit availability relative to drought-hit counties with high credit availability, and the effect persists long after the drought ends.

Manufacturing establishments can cater to demand elsewhere. However, in drought-hit areas, they will be affected by low credit availability (they cannot expand quickly to absorb those exiting agriculture) and the longer run out-migration, which would hurt their labor supply. We find evidence of negative spillovers to the manufacturing sector from the drought in areas with low credit availability. Once again, the effects leave their shadow long after the drought ends.

This paper builds on a rich literature that uses droughts and other climate shocks to evaluate predictions from economic models (Ramcharan 2007). Most closely related is (Hornbeck 2012) on soil erosion during the Dust Bowl, and its effects on migration. Hornbeck does ask whether access to finance (as proxied for by the number of banks in 1928) allows more soil-eroded counties to adjust their mix of agricultural activities faster, and finds mixed results. He does not examine the relationship between access to finance and migration. Turning to papers that focus more directly on credit supply, Cortes and Strahan (2017) study how multi-market banks respond to a variety of natural disasters, and find that they increase lending in affected areas, but reduce lending to unaffected areas, especially ones peripheral to the bank's core locations. Cortes (2014) examines the rebuilding process after a natural disaster, and finds that areas with a one standard deviation more local deposits experience between 1 to 2% less employment loss for young and small firms. Morse (2011) finds that in areas served by payday lenders, poor residents face fewer foreclosures following natural disasters. Berg and Schrader (2012) use volcanic eruptions in Ecuador as an exogenous shock to credit demand, and find those firms with stronger bank relationships have more access to credit. Taken together, these papers suggest access to credit helps areas affected by natural disasters to cope better.

Like Hornbeck (2012), our paper focuses on a climatic event with long term implications for the viability of a key economic activity (agriculture) in the area. Our outcome measure, population growth over the short and long run, reflects the failure to preserve livelihoods or create new ones – a central concern for climate adaptation. In contrast, many of the aforementioned papers focus on the actual damage by disasters to the local area and its repair, not on whether the long run viability of existing livelihoods is fundamentally altered. So in those papers, credit (for rebuilding or repair), investment, or short term unemployment are the appropriate outcome measures given the nature of the shocks. For us, they are only intermediate measures, which help us understand how adaptation takes place. Also, given the nature of the event, existing sources of income and wealth should help localities adapt even if they do not have access to credit, and indeed they do. Given income/wealth and credit are substitutes, it is therefore essential that we show in our analysis that credit supply does not simply proxy for these other attributes of a locality.

In sum, our focus, unlike in Hornbeck (2012), is on the effect of access to finance on climatic adaptation; it adds to the finance papers cited by focusing on the effect of credit supply on livelihoods in the face of a longer-term climatic shock; and it tackles concerns about credit supply proxying for other factors. Moreover, our work shows that when local communities have sufficient access to external sources of finance—in this case bank credit—and the physical means to adapt—through groundwater irrigation in our particular setting—climate shocks can speed innovation and lead to positive long-run outcomes.

From a policy perspective, given the growing concern that mitigation efforts will be insufficient to prevent climatic catastrophes from increasing in frequency and impact, adaptation becomes a more important focus. Our findings then suggest that one way to help poor countries, which are most deeply affected by climate change (in part because they are so dependent on agriculture), is to improve their people's access to finance, especially when physical adaptation is possible within the local community. A related finding in our work is that this can help limit the extent of climate-induced migration, especially to parts of the world that are unprepared to absorb migrants. Also, while financial regulators need to calibrate carefully the possible risks to the banking system from climate-related losses, which would suggest less lending to climate sensitive areas and sectors, this needs to be set against the benefits of credit access in facilitating adaptation and innovation.

Section 1 of this paper develops the main hypothesis and describes the data, while Section 2 presents the basic results. Section 3 focuses on identification; Section 4 studies the investment and technology adjustment margins, while Section 5 concludes.

1. Hypothesis and Data

1.1. Droughts as adverse shocks

Technically, droughts are prolonged exogenous interruptions in rainfall that can disrupt agricultural production and broader economic activity. A drought is thus a close empirical analog to the theoretical productivity shocks in models of business cycle fluctuations. Droughts may also signal possible climatic conditions in the future, and thus may have persistent effects beyond their actual duration. An empirical setting using droughts is thus a useful laboratory to study the role of access to credit in shaping an economy's long run adjustment to an adverse shock.

To this end, we focus on the "1950s" drought, which began in July 1949 and lasted through September 1957. This drought was the second most severe drought of the 20^{th} century after the "Dustbowl" of the 1930s (July 1928-May 1942), and remains the third most severe drought to affect the continental US since 1895—the 2012 drought is now the most severe drought since 1895 (Heim 2017). Unlike the Dustbowl, which occurred during the Depression, the 1950s drought did not occur at a time of general economic distress, and so we can tease out the specific effects of the drought without having to deal with broader confounding factors of a depression. Unlike the 2012 drought, enough time has passed since the 1950s drought to examine longer run consequences. Also, farm output accounted for much more economic activity in 1950 than in 2012 (farm output was 10.4% of US GDP in 1950, with a significantly greater presence in interior rural areas, and only 2.4% in 2012), suggesting another reason to focus on the earlier drought to get a sense of the effects of large-scale climatic disruption on the climate-vulnerable Global South.

Figure A1.1 in the Internet Appendix (IA) shows the time series intensity of droughts, plotting the percent of the continental US land area classified as in drought from 1900-2014. In terms of land area affected, the Dustbowl is only slightly larger than the 1950s drought; the peak coverage of the Dustbowl was 64.5% of the US land area versus 60.9% for the 1950s drought. IA Figure A1.4 shows the spatial variation in drought intensity across the continental US for both the Dustbowl and 1950s droughts. While the Dustbowl mainly affected the upper-Midwest and plain states, the 1950s drought was particularly severe in the southern regions of the United States. In states such as Texas for example, the 1950s was the most arid period in the modern era.

The Standardized Precipitation Index (SPI) is a widely used indicator of drought (Guttman 1999). The SPI is a probability-based measure of drought based on the deviation of precipitation over a particular time period from its historical distribution. The SPI is thus comparable across space, and can be measured at different time scales. For example, an SPI that measures precipitation deviations from its historical mean at a 3 month frequency measures soil moisture conditions, while SPI indices based on a longer time scale, such as the 9 month deviation in precipitation from its historical average, captures more chronic drought conditions that impact soil moisture, as well as ground water and reservoir storage.[4]

In this paper, we use county-level data from the National Oceanic and Atmospheric Administration (NOAA) on SPI indices that use a 9 month time scale to measure the percent of a county's land area that is in exceptional drought, defined as "exceptional and widespread crop/pasture losses" and "shortages of water in reservoirs, streams and wells creating water emergencies". These data are available monthly from 1895 through the current period. The main drought metric used in the analysis is the average percent of a county's land area in exceptional drought over the period 1949-1959. For example, if on average 20 percent of a county's land area was in drought over the 1950s, then this variable would equal 20. IA Table A1.1 reports summary statistics for this measure for the nine standard geographic Census regions. Consistent with the graphical evidence based on the PDSI, the 1950s drought was mainly concentrated in the Southwest and Mountain states while the Dustbowl affected the upper Midwest through the mid-Atlantic region.

1.2. Hypothesis

That access to credit could help regions adapt to adverse shocks is not surprising. The primary objective of the empirical work will be to establish how precisely access to credit affects adaptation, whether there are long run consequences, and what forms these take.

Survival

A large theoretical literature has argued that financial frictions can propagate and amplify the impact of productivity shocks on the real economy.[5] There are various channels through which this can work. An adverse shock that reduces cash flows and collateral values also reduces an enterprise's borrowing capacity, especially in the presence of financial frictions that prevent the full present value of an investment from being pledged to financiers. Not only does this lead to

[4] The Palmer Drought Severity Index (PDSI) is another common drought measure. The PDSI is a single index that uses the water balance for a particular area—precipitation, evapotranspiration, runoff and soil moisture—to calculate local drought intensity. See https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-index-spi for a short description of drought measures.

[5] See for example the macroeconomics literature emanating from (Kiyotaki and Moore 1997) and (Bernanke and Gertler 1989, Bernanke, Gertler et al. 1999). Richer formulations of this insight that incorporate lender balance sheet dynamics and asset prices include (Gertler and Kiyotaki 2011, He and Krishnamurthy 2013, Brunnermeier and Sannikov 2014, Gertler and Kiyotaki 2015). A non-exhaustive list of major contributions at the intersection of corporate finance and macroeconomics include (Whited 1992, Cooley and Quadrini 2001, Hennessy and Whited 2005, Cooley and Quadrini 2006, Jermann and Quadrini 2012).

pro-cyclical investment as the "credit channel" literature observes, it could lead to increased liquidation risk of solvent businesses as they are unable to service debt.

Investment

Indeed, the adverse shock may itself require credit-enabled spending by enterprises for their own survival. For instance, farms may need key inputs like new seeds and fertilizers to keep production going. Farmers with little revenues may also need to borrow to pay workers and put food on the table for their own families. Credit-enabled spending that helps farms survive is likely to have high private and social returns, especially if it preserves human and organizational capital. Farm failures were indeed of great importance during the 1950s Drought. Texas lost nearly 100,000 farms and ranches over the 1950s, with losses in the agricultural sector exceeding those of the Dust Bowl years.

An adverse shock such as a persistent drought may also increase the return from alternative investments, for instance from sowing drought-hardy crops, which are a form of adaptation to the changed production conditions. Furthermore, to the extent that production has to be curtailed during investment because key inputs to production are unavailable (for example, because farmer labor is devoted to supervising the investment or land cannot be planted as irrigation pumps are being installed), a time of low productivity may imply a low opportunity cost in terms of lost production and hence greater effective returns to investment (Aghion, Angeletos et al. 2010).

Indeed the need to invest to adapt, coupled with the lower opportunity cost of investment, may allow farmers in drought-hit areas with better credit access to *leapfrog* technologically. For instance, farmers with the financing capacity to afford both the installation and working capital costs might be expected to adapt to the drought by installing irrigation equipment, especially the then newly developed center pivot irrigation system, even before areas with no drought.[6] Calamity, when confronted with adequate financing, might lead to earlier adoption of technology.

Investment may also trigger complementary investments. A shift to irrigated agriculture can reduce uncertainty about future water supply. And this reduced uncertainty can make it optimal for farmers to undertake other large irreversible investments in mechanization that can further allow them to adapt to the drought and increase long-run productivity (Bern, Quick and Herum 2019). Notably, the 1950s were a period of rapid technological change in farming equipment,

[6] See for example (Matsuyama 2007) and the surveys in (Matsuyama 2007, Aghion and Howitt 2008).

and the use of these technologies could compensate for the drought-induced decline in productivity (and labor). For example, tractor and truck horsepower increased sharply as manufacturers improved engine technologies in the wake of WWII.[7] Also, the adoption of new water efficient hybrid sorghum seeds made it profitable for some farmers to also invest in new irrigation technology, and this joint adoption could thus significantly raise farm productivity (Kremer 1993), increasing the importance of credit availability in shaping adaptation to the drought. There may also be spillovers to others from the complementary investments triggered by the drought, raising the possibility of the drought serving as a coordinating signal to move to a new equilibrium.

Ownership

Land ownership and farm sizes might also be altered with the drought. Farmers could increase farmed acreage to compensate for lower yields. Access to credit would again facilitate such investment, which would imply an increase in land devoted to agriculture and the expansion of the size of existing farms in drought affected areas with access to credit. The increased capital investment in farming would also push towards increased scale.

Of course, because small marginal farms (especially tenant farmers, who did not have enough wealth to own their farms and therefore would have little pledgeable collateral) would also be able to survive in areas with easier access to credit, the effect of easier access to credit in drought-prone areas on average farm sizes would be ambiguous.

Spillovers

Easier access to credit could also result in sectoral and geographic spillovers. Specifically, the survival and continuing presence of marginal farmers as well as the expansion of large farm production in drought-stricken areas with access to credit could result in more jobs and preserved livelihoods. These could create stronger demand for goods sold by retail and other non-traded local businesses, preserving jobs in those sectors also.

More jobs in areas with credit access may have then drawn migrants from neighboring drought-hit areas with limited credit access. So areas with credit access may have caused negative spillovers for areas without credit access, especially if credit is hard to obtain at a distance.

[7] Anecdotal descriptions of these horsepower increases among tractors can be found at https://www.yesterdaystractors.com/cgi-bin/viewit.cgi?bd=ttalk&th=2251661

Demographics

All these effects would show up in available jobs, local incomes, and hence have demographic consequences through immigration, emigration, marriages, births, and deaths. We will first establish the correlations between drought and demographic outcomes, then explore the mediating effect of credit, and finally examine the channels through which credit availability affects demographic outcomes.

1.3 Credit Data

Small business bank lending is an intensely local business, and agricultural lending even more so. Petersen and Rajan (2002) find that the mean distance between small businesses and their bank lender was 16 miles in the 1970s (median 2 miles), and this had increased with the advent of information technology to 68 miles in the early 1990s (median 5 miles). In 2000, Granja, Leuz, and Rajan (2022) find that the average distance between bank and borrower for all loans is around 200 miles, and the median for all loans is still around 5 miles. The mean distance between borrower and lending branch for agricultural loans is only around 50 miles at this time – so agricultural loans are even more local. Given that communications technology was even less well developed in the 1950s, these findings allow us to restrict our attention to the availability of credit within a town or a county.

While agricultural production occurs in rural areas, incorporated towns were the predominant centers of finance in most counties during this period. We thus first collect data on the balance sheets of all banks headquartered in a stratified random sample of about 1,300 towns across the US in end-1929, 1939, 1950 and 1960—the towns are show in IA Figure A1.2 for the 1950 snapshot of the panel. Note that the number of banks vary in each period of the panel, so that we have 5,621 banks in 1929; 2,985 banks in 1939; 2,896 banks in 1950 and 3,027 banks in 1960. For each bank, we collected basic information on the value of loans, assets, deposits, capital, and other balance sheet variables.

For much of the analysis, we aggregate the bank-level data up to the county-level to construct standard measures of credit availability in a county just before the drought. Our main measure of credit availability just before the drought is the log of loans per capita in a county in 1950. This variable should be higher in areas where banks have historically been better able to overcome information and other frictions in order to establish credit relationships. In turn, higher loans per capita in 1950 suggests that the local banking system would have a greater capacity to increase loan supply to accommodate a drought-related increase in the demand for bank finance.

IA Figure A1.3 shows that loans per capita in the county is strongly positively correlated with the number of banks per 10,000 people in the county—another standard proxy for de facto credit availability. Table 1 summarizes these standard ex-ante credit availability measures in 1950. At the county level, the mean loans per capita is about $115 or about $1,400 in 2022 dollars, and on average, there are about 7 banks per 10,000 people in the county. Towns are geographically much smaller than counties, and these credit availability measures tend to be higher when measured at this more granular level. Because there are a number of small towns in the sample, the variability in loans per capita and the number of banks per 10,000 people also tend to be higher at the town-level.

We focus on local banks because they were an important source of farm credit during this period, especially for working capital and equipment financing (Herder 1970).[8] IA Table A1.2 shows that banks accounted for about 28 percent of all credit flowing into the farming sector in 1950. Banks specialized in working capital and equipment financing loans, accounting for about 40 percent of such loans. Merchants and dealers, such as captive financiers, provided most of the remaining financing for these non-real estate loans. In the case of real-estate loans, banks supplied only about 16.8 percent of mortgage credit in 1950, with life insurance companies and other institutions doing the bulk of mortgage financing. Thus, the potential supply of bank finance is likely to be more useful for farmers investing to adapt to the drought than for land purchases. To the extent, however, that banks monitor on behalf of more passive lenders (e.g., Diamond (1997)), the availability of bank credit should influence all forms of credit.

1.4. Economic and Demographic Data

IA Table A1.3 summarizes some of the US Census data, digitized by Michael Haines, for the counties in our sample. Aggregate measures of adaptation investment are suggestive. There is a large increase in farm acreage under irrigation between 1949-1959 relative to the 1960s, suggesting that farmers adapted to the drought at the intensive margin by reducing their

[8] See the narrative evidence at https://livinghistoryfarm.org/farminginthe40s/money_12.html. For example “"They just probably knew me," he says. "Knew my dad and so forth... [Now] you put down what you want to do, what your costs for different fertilizer, seed and so forth, irrigation. You go through that every year with the bank … and try to see what the bottom line is going to look like at the end of the year. So, they play a part in the role of most farmers."

dependence on rainfed agriculture. However, the 1950s drought decade also saw a mean decline in the amount of land devoted to agriculture, implying that the drought forced some farmers to leave agriculture entirely, and others to abandon unproductive land. We also have data on farm capital equipment such as trucks, autos, and tractors in 1969, the first post-drought year that the Census of Agriculture provides this data.

Adverse productivity shocks like droughts have non-linear effects on agricultural production and local economic activity. A drought of moderate intensity for example makes existing capital—livestock and trees—less productive; it can diminish milk production or harvests, temporarily reducing cash-flow among farms and local businesses. But a more severe drought can destroy the underlying "physical" capital on the farm—killing livestock and trees and causing soil erosion—leading to an increase in demand for both working capital and investment finance in order for farms to survive, replace physical capital, and make adaptive investments.

Therefore, our main measure of extreme drought in the paper will be an indicator variable that equals 1 if a county was in the top quartile of drought exposure between 1949 and 1959. Since drought exposure measures the percent of a county that is in extreme drought stress averaged over the period 1949-1959 (see earlier), this indicator proxies for how widespread and prolonged stress is in a county. For the town-level analysis, we use the same county-level drought indicator.

But first Table 2 corroborates the scientific consensus that the 1950s drought was caused by macroscopic changes in weather systems, and was not correlated with ex ante economic or social attributes of counties. In column 1, the dependent variable in loans per capita, in column 2, banks per 10000 people, and in column 3, population growth in the county between 1940 and 1950 as the dependent variable. The estimated coefficient for the indicator of top quartile stress is economically and statistically insignificant in all cases, suggesting the drought appears to be a random spatial shock.

While the 1950s drought is unrelated to the ex-ante spatial variation in banking access, droughts tend to be serially correlated. It is thus possible that areas exposed to the 1950s drought—the arid south west for example—might also have had past droughts or greater rainfall variability—such as the Texas hill country. And these previous periods of arid conditions could both shape the variation in credit access by 1950, and adaptation to the 1950s drought itself. We directly check for this possibility in our subsequent empirical tests, but the remaining columns of Table 2 suggests this concern maybe of limited empirical relevance. These columns regress the previous measures of banking access on both the mean and standard deviation of a county's land area in drought between 1895 and 1926—the years spanning the beginning of data collection to just before the onset of the Dust Bowl. As with the 1950s drought itself, these variables are individually and jointly insignificant. We next examine the role of access to bank finance in mediating the demographic impact of the drought.

2. Basic results on drought exposure and the impact of credit

2.1 Demographic Outcomes—County-Level Evidence

In Table 3 we study the interaction between access to finance and drought exposure on population growth at the county-level between 1950 and 1960. The baseline specification interacts county *i's* drought exposure, D_i, with the county's log per capita loans in 1950, C_i:

$$(3) \qquad \Delta population_i = \beta_0 + \beta_1 D_i + \beta_2 C_i + \beta_3 D_i * C_i + \beta_4 X_i + \beta_4 D_i * X_i + e_i$$

where β_3 measures the role of credit in mediating the impact of the drought. If, for example, emigration is weaker in drought exposed counties in which the local population can obtain significant additional bank credit to adapt to the shock, then $\beta_3 > 0$. Because per capita loans might be related to a county's pre-existing population and other factors, X_i, the baseline specification also allows the drought's impact to vary with X_i.

To show simply that the 1950s drought exposure affected demographic outcomes, column 1 of Table 3 estimates the direct impact of the drought on population at the county-level, with state fixed effects also included as explanatory variables. The sample consists of all US counties with available drought intensity data. The drought measure is the continuous SPI based measure of the mean percent of a county's land area affected by extreme drought over 1949-1959. The point estimate on drought intensity is statistically significant (p-value=0.03) and economically large—the binscatter plot in panel A of IA Figure A1.5 displays the relationship estimated in column 1. The point estimate implies that moving from a county at the 10th to 90th percentile of drought intensity is associated with a decline in the county's population growth of about 3.6 percentage points between 1950-1960; the absolute value of this magnitude equals the mean population growth over the period or about 0.16 standard deviation.

We have hand-collected bank lending data for about 1,300 towns and cities across 993 counties, and column 2 of Table 3 restricts the sample to these counties. The implied effect of the drought on population growth is similar to the full sample. Moving from a county at the 10^{th} percentile of drought intensity to one at the 90^{th} percentile is associated with a decline in the county's population growth of about 5.2 percentage points between 1950-1960; the absolute value of this magnitude equals 80 percent of the mean population growth over the period or about 0.25 standard deviations in this subsample of counties.

Column 3 allows the impact of the drought on population growth to vary depending on the county's quartile of drought exposure. The bottom quartile—those counties least exposed to drought conditions over the 1950s—is the omitted category. The evidence suggests that the drought's impact on population growth is highly non-linear. Top quartile exposure is associated with a 6.6 percentage point reduction in population growth. Moreover, while the second and third quartile indicator variables are negative, they are not significant. In order to more easily exposit the evidence, in what follows, we use the top quartile drought indicator as the main measure of drought exposure.

Using a parsimonious version of this non-linear specification, column 4 provides preliminary evidence that access to bank credit might moderate the impact of severe drought exposure on population growth. We include an interaction of top quartile exposure indicator with the log of per capita bank credit in the county in 1950. This standard proxy for credit access is expected to be higher in counties where banks have more active credit relationships and residents can more easily obtain bank credit—counties where there are fewer information and spatial frictions to intermediation. We also include each of these variables directly.

However, a concern with the log of per capita bank credit as a proxy for credit access is that this variable could vary mechanically with the population or physical area of the county. For example, a county's population can independently shape the economic impact of the shock. Notably, a small county might have a large per capita stock of loans on account of a few large borrowers. At the same time, because of its small size, the county might also have a much less spatially- and sectorally diversified economy. Because it is unlikely to be able to absorb surplus farm labor, a small county would be particularly susceptible to a severe drought. To exclude these forms of mechanical bias, we also include in column 4 linearly the log of population in

1950 and the log area of the county as well as the interaction between these variables and the top quartile drought indicator. This is the baseline specification henceforth**.**

The estimates in column 4 of Table 3 suggests that bank credit access attenuates the economic impact of adverse productivity shocks. Holding constant the population of the county in 1950, the estimates in column 4 show that for a county at the 10th percentile of the log of per capita loans in 1950, top quartile drought exposure is associated with a 6.3 percentage point decline in population growth relative to otherwise (p-value=0.01). But for a county at the median level of the per capita credit distribution, top quartile drought exposure is associated with only a 1.5 percentage point decline, which itself is not different from zero (p-value=0.41). Panel A of Figure 1 plots the marginal impact of the drought on population growth over the distribution of log per capita bank credit in 1950.[9] Going forward, we will report the marginal impact of top-quartile drought exposure for the 10th, 50th and 90th percentiles of the credit distribution. The associated p-value measures the likelihood that a particular marginal effect is different from zero. These marginal effects are always evaluated at the mean of population and any other covariate that is also interacted with the drought indicator variable.

Loans per capita can proxy for per capita wealth, income or myriad factors that can also attenuate the economic impact of adverse productivity shocks. We address these identification concerns in later sections, but the remaining columns of Table 3 first assess the statistical robustness of the interaction with access to credit to alternative explanations and assumptions. Counties differ in size, and column 5 addresses heteroscedasticity by using weighted least squares based on county population in 1950 for the baseline sample of counties. The point estimates are slightly larger, and we use the more conservative unweighted approach in the subsequent analysis.

We next allow the marginal impact of the drought to depend on a wide range of potentially important geographic and income confounders. Notably, the supply of local surface water for agriculture is greater in counties east of the 98th meridian, and in part this geographic fact led to different settlement densities and water rights practices across the US, which in turn could affect these results (Libecap and Dinar 2022). To partially address this concern, column 6 interacts the

[9] Instead of using a top-quartile indicator variable to measure drought exposure, Figure A1 in the appendix uses an above median indicator variable and plots the marginal impact of exposure, based on this above median indicator variable, over the distribution of log per capita bank credit in 1950. The effects are very similar as the coefficient on the interaction term is 0.035 (p-value=0.02).

drought indicator variable with the mean rainfall in the county; the standard deviation of rainfall; mean snow fall; the standard deviation of snowfall; the log of county area; the log of median income in the county in 1950; the share of rural population in 1950 and the log population in 1950. The regression also includes log deposits per capita in 1950 to better control for the self-insurance capacity of local farmers through their existing savings. All variables are also linearly included.

The regression in column 6 thus allows the marginal impact of top-quartile drought exposure to depend simultaneously on 10 different factors. Because of multicollinearity, the direct effect of the drought is no longer significant, but despite the large number of controls, the marginal impact of credit availability remains economically similar to the baseline effect.[10] Note that including extra interaction terms for whether a county's centroid lies west of the 98th meridian—an indicator variable, as well as a county's past aridity—the 1895-1926 mean and standard deviation of the county's land area in drought—Table 2—has no impact on the marginal effect of loans per capita reported in column 6.

Column 7 of Table 3 uses the baseline specification to examine the role of credit access in long-run outcomes. If people returned to their counties after the drought ended, then the mediating impact of finance, though large, might be temporary. However, if people migrate away from drought-affected counties with little access to bank finance, and remain in those areas after the drought ended, perhaps to avoid incurring the costs of returning or because they have moved to more attractive and resilient locales, then population losses will be permanent.

To check for persistence then, the dependent variable in column 7 is the change in population between 1950 and 1980—a generation since the drought. The implied effect of the drought and access to finance is even larger in the long run. For a county at the 10th percentile of the log of per capita loans in 1950, top quartile drought exposure is associated with a 10.3 percentage point decline in population growth over the 30 years (p-value<0.00). Even at the median distribution of bank credit, drought exposure is associated with a 4.8 percentage point decline in the 1980 population relative to 1950 (p-value=0.07).

Panel B of Figure 1 illustrates this long run divergence of population outcomes. Using the coefficients in column 7, the figure plots the predicted change in population at different points in

[10] The weather variables are averages over the 20th century. The point estimates for these additional controls are available upon request.

the bank credit distribution separately for top-quartile drought-exposed and non-top-quartile counties. The figure shows that ex-ante bank credit has a weak association with population growth among non-drought exposed counties, but a significantly larger one among drought exposed counties. For example, for two drought exposed counties with identical populations in 1950, the 1980 population is about 7 percentage points higher for the county at the 90th percentile of the bank credit distribution relative to one that was at the 10th percentile. But for counties not exposed to the drought, this difference in the 1980 population between the 90th and 10th percentile is neither statistically nor economically significant. In other words, lower credit availability interacts with the drought shock to induce long run economic divergence.

This divergence in long run demographic outcomes can arise from both permanent net migration away from drought exposed counties with limited access to credit, their contribution to fertility in the host location, as well as reduced fertility among the population that experiences the emigration. Fertility among the remaining population can decline, for example if the remaining population are older and past the child-bearing age, or are less able to afford children because of their diminished economic circumstances. Table 4 examines these different adjustment margins, focusing on migration and births and deaths. The dependent variable in column 1 is the percent of the population in a county in 1960 that emigrated from a different county prior to 1960, that is, domestic migrants. As the bottom panel suggests, top quartile drought exposure is associated with a 1.67 percentage point decline in the percent of domestic immigrants into a county (p-value=0.04) for a county at the 10th percentile of the log of per capita loans in 1950. But at the median of the ex-ante credit availability distribution, the negative impact of the drought becomes much smaller and statistically insignificant.

The dependent variable in column 2 is the number of per capita live births in the county in 1960. Column 2 also includes the log number of per capita live births in the county in 1950 to absorb pre-existing differences in fertility across counties. Top quartile drought exposure is associated with a 3 percentage point drop in the number of live births in 1960 for a county at the 10th percentile of the log of per capita loans in 1950 (p-value=0.03). But at the median of the ex-ante credit availability distribution, the negative impact of the drought is again small and insignificant. Column 3 provides suggestive evidence of persistence, as fertility is also higher in 1980 in drought exposed counties with higher levels of ex-ante credit availability. For example, births per capita is about 2.8 percent higher in 1980 among drought exposed counties at the 90th percentile of the credit distribution, and this impact is different from zero (p-value=0.05).

Not only does fertility decline in drought exposed counties with limited access to credit, but Table 4 shows that deaths per capita also are higher in these counties, especially long after the drought ended. From column 4, top quartile drought exposure is associated with a 2.9 percentage point increase in deaths per capita in 1960 for a county at the 10th percentile of the log of per capita loans in 1950 (p-value=0.11). But in 1980, the marginal effect of drought exposure on death rates jumps to 8.7 percentage points for counties at the 10th percentile of credit (p-value=0.01), and is large and significant even for counties at the median level of bank credit (column 5).

We have shown there is less immigration, fewer births, and higher death rates in counties with high drought exposure and low access to credit, and IA Table A1.4 examines the impact of the drought on the age distribution in the county. The dependent variable in column 1 of IA Table A1.4 is the percent of the population in 1960 that is less than 20 years old. Consistent with the decline in fertility seen earlier in column 1 of Table 4 and the possible emigration of families with young children, the marginal impact of drought exposure on the fraction of the population less than 20 years old is statistically negative but small in magnitude in counties with limited access to credit.

Columns 2 and 3 of IA Table A1.4 examine both ends of the adult age distribution. The dependent variable in column 2 is the fraction of the population in a county between 20-29 years in 1960, while the dependent variable in column 3 is the fraction older than 69 years, also in 1960. In keeping with the prediction that the young are more likely to emigrate away from areas where credit is insufficient to foster adaptation, the fraction of 20 year olds decline in drought exposed counties with limited credit access, while the fraction of over-69 year olds rises in these areas. Columns 4 and 5 illustrate this prediction more generally, showing that the median age in the population increases relatively more in drought exposed counties at the bottom of the credit distribution in both 1960 and in 1980**.**

Taken together, when credit access is limited, drought exposed counties experience relative long-run demographic decline. We repeat the analysis of Table 3 for town population growth. It is in IA Table A3.1. The economic magnitudes are similar to those obtained using county-level data.[11] Unfortunately, we do not have the details of demographic composition in each town and cannot repeat the analysis in demographic and age analyses.

2.3. Credit Outcomes—Town-Level Evidence

There is, however, an advantage of using incorporated towns as the unit of analysis in that they were the predominant centers of finance in most counties during this period. This granularity allows us to measure better any bank supply response that is unique to the drought and not part of longer-term local trends. The key prediction is that if credit availability indeed shaped the demographic impact of the drought, then towns with smaller ex-ante credit constraints should also experience a relatively larger increase in drought-related lending, as in-town banks expand credit supply in order to meet drought-related credit demand. But in towns where ex-ante credit constraints are large, so that lending is closely linked to borrower net worth or credit relationships weak , bank lending should decline in response to the drought-induced decline in farm cash-flow and asset values.

Table 5 examines the impact of drought-exposure and ex-ante credit availability on credit and other bank outcomes. The dependent variable in column 1 is the change in bank lending between 1950 and 1960 scaled by total town-level bank assets in 1950. Column 1 shows that drought-exposure is associated with increased bank lending in towns with greater ex-ante credit access. But for towns with low ex-ante credit access, drought-exposure is associated with a sharp relative contraction in loan growth. For a town at the 10th percentile of the per capita bank credit distribution in 1950, drought exposure suggests a 30.6 percentage point decline in lending over the next 10 years (p-value=0.01), but for a town at the 90th percentile of this distribution, the impact of the drought on lending is positive, at 14.5 percent, but not significantly different from zero (p-value=0.27).

The evidence in column 1 might reflect "pre-trends" in bank lending rather than the local banking system's supply response to the drought. That is, the spatial variation in drought-exposure is random, but the decades immediately after WWII was a period of rapid economic growth in the US, and the variation in town-level drought-exposure might coincide with pre-existing trends in credit growth. To address this concern, column 2 replicates the specification in

[11] Also, because droughts are spatial shocks, they can induce dependence in the standard errors based on the spatial proximity of towns. To address this concern, we use the procedure described in (Conley 1999) to adjust the standard errors for possible spatial dependence. These results are in Appendix Table A2.2; the main findings are robust to a wide range of distance-based dependence assumptions.

column 1, but for lending growth between 1940 and 1950—the decade before the drought. The drought indicator variable, along with the interaction term with per capita credit in 1940 are individually and jointly insignificant. The implied magnitudes are also tiny. This finding is important for it suggests the differential ability of the banking system to respond to the emergency need is the primary factor associated with different outcomes – the difference is less likely to be associated with permanent structural differences in credit delivery. Put differently, it is the interaction of credit availability with the drought shock rather than credit availability alone that seems to be associated with different outcomes.

As a further check of the supply response interpretation, column 3 uses the loans to assets ratio in 1960 among in-town banks as the dependent variable. The evidence suggests that these results do not reflect a general balance sheet expansion among banks, but a shift in the composition of banks' assets towards loans in response to drought-related credit demand. For a town at the 10th percentile of the per capita credit distribution in 1950, drought exposure suggests a 4.8 percentage point drop in the loans to assets ratio in 1960 (p-value=0.01). But for towns at the 90th percentile of the distribution, loans to assets increased by 4.6 percentage points (p-value<0.00).

Droughts can affect bank liquidity and capital and both the liquidity and capital channels can also affect loan supply (Diamond and Rajan 2005, Brunnermeier and Sannikov 2014). In particular, if banks mainly relied on local deposits to fund loans, then a drawdown in deposits in response to the drought could impair bank lending and lead to inefficient loan sales, especially if these institutions lack liquid assets. Similarly, drought-related loan losses could erode bank equity and also reduce lending.

We have already seen that controlling for deposits at the county-level does not alter these results (column 6 of

Table 3), but to check these alternative channels, column 4 of Table 5 includes the change in deposits in the town between 1950-1960, scaled by assets in 1950, as well as the change in total bank capital over the decade, scaled by assets in 1950. We also include the interaction of these variables with the drought indicator. Neither the marginal estimated impact of drought exposure on lending, nor the point estimate on the loans per capita in 1950 interacted with the drought indicator, change appreciably relative to column 3, which presents the same regressions without these additional controls.

3. Identification

The evidence thus far is consistent with credit availability affecting adaptation, but there are other compelling alternative interpretations. One obvious candidate is that the 1950 per capita bank credit variable might proxy for per capita wealth or income, and our results might reflect the fact that populations in wealthier counties or towns have greater sources of internal liquidity to adjust better to the drought. Also, because bank credit might be more plentiful in larger more diversified counties or towns, these results might reflect the availability of more non-farm economic opportunities that allow populations to remain in a drought-affected area rather than migrate. We now suggest tests that offer greater evidence of the causal effects of credit availability, and help distinguish between these alternative interpretations.

3.1. Capital requirements

During the sample period, states and the federal government used "place-based" minimum capital requirements to regulate bank entry (Walter 2019). These minimum capital requirements were set at the level of the incorporated town in which the bank was headquartered and based on the population of the town, as recorded in the last decennial census. For instance, California required banks to maintain a minimum of $25,000 in capital if they wanted a state-charter in a town with less than 6,000 people; $50,000 if the town's population was between 6,000 and 25,000; $100,000 if the population was between 25,000 and 50,000 people; the capital requirement rose to $200,000 if the population exceeded 50,000 people. These regulations varied sharply across states. In Alabama, state-chartered banks could be opened with $15,000 capital if the town's population was below 3,000, but this capital requirement increased to $25,000 if the population exceeded this 3,000 threshold. The federal government's minimum capital requirements applied only to national banks and did not vary across states.

3.1.1 First stage argument

The identification strategy uses the plausibly exogenous town-level variation in credit availability in the 1950s stemming from these place-based policies since circa 1910. After the outbreak of WWI, there was a sharp expansion in the number of state-chartered, and to a lesser extent, national banks. As shown in IA Table A4.1, the number of state banks expanded by roughly 43 percent between 1910 and 1920, while the number of national banks increased by about 14 percent. This expansion was fueled in part by a boom in world commodity prices and competition between the state and national banking systems. The expansion ended in the early

1920s amid the world collapse in commodity prices, leading first to a wave of banking failures throughout the 1920s and then the near collapse of the banking system in the Great Depression[12]

These facts imply that towns subject to higher entry capital requirements on account of state regulations and the size of the town's population in 1910 would likely have fewer but larger and better capitalized banks. These bigger and better capitalized banks would in turn be more likely to survive the 1920s commodity bust and the banking shocks of the Great Depression. Because of these differences in survival rates based on local regulation and bank size, towns with higher capital requirements circa 1910 would be left with relatively more banks and a greater potential supply of bank credit in the post-Depression era.

IA Table A4.2 shows that by 1929—about 8 years after the initial collapse in commodity prices—towns with higher capital requirements in 1910 had more banks per capita in 1929. The relationship between the 1910 capital requirement and bank survival sharpens after the banking panics of the Depression. Towns with higher capital requirements before the Depression had more banks after the Depression-era wave of bank failures through 1950. Note that we control for population in 1910. In IA Table A4.3 we regress the log credit per capita in 1950 on the 1910 capital requirement and a variety of ways of controlling for population in 1950. The coefficient estimate on the 1910 capital requirement is always positive and statistically significant. Further motivating this approach is the fact that town-based capital requirements were instituted well before the 1950s drought itself. And once established circa 1910, most state-level regulations did not change again until the 1980s with the modernization of banking regulation. Specifically, they did not change in response to population dynamics in specific towns over the subsequent decades. These state regulations emerged in part from states' desire to expand the number of state-chartered banks relative to national banks in order to retain state-level control over the local banking system. Thus, state-fixed effects absorb the state-level political economy factors behind the state-level variation in capital entry regulations.

Building on this evidence, the first-stage specification regresses the log of loans per capita in 1950 on the log of a town's 1910 capital requirement, as determined by state regulation and the town's 1910 population. The first stage includes all the baseline covariates: the drought indicator variable interacted with the log population of the town in 1950, as well as their linear components along with state fixed effects. As reported in the bottom of Table 6, the coefficient

[12] See the discussion in Rajan and Ramcharan (2015, 2016).

on the log 1910 capital requirement in this first stage regression is 0.295 with an F-statistic of 7.22 (p-value=0.01). Across a range of specifications then, a town's 1910 capital requirement helps to determine the town-level variation in credit availability in 1950. We next use this source of conditionally exogenous variation to assess the consistency of the OLS estimates.

3.2.2 Second stage results

Table 6 efficiently handles the possibly endogenous per capita credit variable in the non-linear baseline specification using a control function approach. This approach includes the residual from the first stage regression to directly control for shocks to the log of per capita bank credit. Note that as with the instrumental variables estimator, the control function approach yields unbiased estimates under the maintained assumption that a town's 1910 capital requirement influences population growth between 1950-1960 exclusively through per capita bank credit. The specifications in Table 6 are otherwise identical to the baseline: they all directly control for log population in 1950 and interact this variable with the top quartile drought exposure indicator as well; all regressions include state-fixed effects. The standard errors are bootstrapped and clustered at the state-level.

The dependent variable in column 1 is the change in bank lending, while column 2 uses the change in population growth, all over 1950-1960. Column 3 uses population growth over 1950-1980. In all cases, the first-stage residual is insignificant, and the control function approach yields estimates economically and statistically similar to the previous OLS estimates.[13] While this evidence suggests that credit can causally shape the demographic impact of a large climate shock, these tests do not identify a particular mechanism. Credit access can for example allow farmers to better adapt to drought conditions through investments in irrigation and automation. But pre-existing differences in credit access across towns or counties might also induce differences in the diversification and scale of local economic activity. Therefore, rather than loan supply, these results might reflect these differences in economic diversification, as induced by credit, that determine the capacity of local economies to handle a long drought. We therefore next develop a sequence of tests to isolate better the mechanism underlying the relationship between credit and drought exposure.

[13] These results are similar if we use the 1920 capital requirement to construct the control function—the first stage coefficient is also 0.291 and the F-statistic is 8.66 (p-value<0.01).

3.2. Bank credit supply at the border

Our second identification strategy makes use of bank lending frictions at state borders. Our entire analysis is based on the evidence that small business bank lending, especially bank lending to agriculture, is intensely local. Furthermore, until the deregulatory waves of the 1980s, interstate branching was largely prohibited. To the extent that a migrating borrower had to stay near their bank's network of branches in order to avail of the bank's knowledge about them and obtain additional credit, this would limit migratory options.

Furthermore, it was difficult to lend across state borders. Concerned about the illiquidity of real estate collateral, states severely restricted the types of mortgage-related transactions that their banks could engage in across state lines, imposing limits for example on the types of properties that could be used as collateral, aggregate limits on out-of-state exposures, as well as more general limits on the size and duration of the mortgage portfolio (Weldon 1910; Barnett 1911).

Perhaps most difficult was registering and seizing collateral across state lines (The Bankers Encyclopedia 1920). Until the promulgation of the Uniform Commercial Code in most states starting in the late 1950s (see Braucher (1958)), collateral registration and foreclosure laws and practices differed across states, making it difficult for an out-of-state lender to establish the priority of their claim, as well as to seize collateral that had been pledged to them. Nearby in-state lenders with lawyers admitted to the state bar could more easily assess claims and imminent distress, as well as seize collateral, resulting in lower losses given default relative to equidistant banks lending across state lines. As a result, bank credit across state lines was significantly attenuated relative to bank credit within state (Rajan and Ramcharan (2015)).

If credit markets are extremely local, credit availability in even moderately distant towns or counties should not matter for credit conditions in the local market. However, to the extent that their original bank's network of branches (and correspondent banks) extends to other nearby locales, borrowers might still be able to migrate and obtain fresh credit in their new location from local lenders there. These lenders would get to know the borrower's credit history from the network, and if in-state, would be able to handle the borrower's past loans and collateral pledges, even while lending against new assets. So we would expect that if the prospect of starting afresh elsewhere drives outmigration, in-state locations with strong credit availability would be particularly attractive if credit were an important factor, while equidistant out-of-state locations with strong credit availability would not.

This logic is the basis of our second identification test. Unlike the first test, which examines exogenous factors determining the local availability of credit, this test examines whether the relative availability of credit nearby affects migration – are towns in drought affected areas with little credit availability more likely to lose population when situated near towns with plentiful credit availability compared to towns in drought affected areas with plentiful credit availability (and therefore little need for migration in search of credit). What will identify whether credit is the driving force is whether in-state towns have greater influence than out-of-state towns.

Importantly, if per capita bank credit in 1950 proxies for income, local economic diversification or some other latent factor, then state borders should be largely irrelevant in shaping the impact of the drought. For instance, if per capita credit proxies for income or non-agricultural sources of employment, then people in drought affected towns seeking better economic opportunities could just as easily migrate to higher income nearby towns in-state, or to equidistant higher income towns across the state border. So if per capita bank credit in 1950 proxies for income, the coefficient on in-state per capita bank credit in 1950, computed over nearby towns, interacted with drought exposure should be similar to the coefficient on per capita bank credit in 1950, computed over equidistant out-of-state towns, interacted with drought exposure. These border discontinuity tests thus provide a useful way to distinguish the ex-ante credit availability channel from these alternative interpretations.

To implement these tests, for each town in the sample, we locate all towns within a 200 mile radius of a reference town and in the same state, and then compute the mean per capita credit among these nearby towns in 1950. Similarly, we locate all towns within the same radius of the reference town, but across the state border and compute the mean per capita credit among that subsample of towns. The baseline estimation includes these two additional variables linearly, as well as interacted with the top quartile drought exposure indicator variable of the town in question. To exclude mechanical size effects, this regression also computes separately the total population of the towns in the 200 mile radius, in-state and out-of-state, and interacts these variables with the drought indicator as well; we continue to interact the town's population with drought-exposure as well.

The dependent variable in column 1 of Table 7 is population growth in a town between 1950 and 1960. As before, the negative impact of drought exposure is smaller when in-town credit constraints are small. At the 10th percentile of the in-town loans per capita distribution, drought exposure suggests a 9.6 percentage point decline population (p-value=0.02). But at the 90th percentile, exposure suggests a 3.7 percentage point increase in population (p-value=0.45). However, consistent with the migration hypothesis, the negative impact of drought exposure on a town's population growth is larger when nearby in-state loans per capita is large. At the 90th percentile of loans per capita among in-state banks within a 200 mile radius, drought exposure suggests a 7.9 percentage point drop in population growth (p-value=0.07). Strikingly, the coefficient on loans per capita among equidistant out-of-state banks is about 5 times smaller and not significant (p-value=0.59).

Nearby in-state centers of bank finance are likely to attract migrants when loans per capita in these towns is large relative to the size of lending capacity in the drought-affected town itself. Column 2 evaluates this prediction using a triple interaction term. This specification interacts drought exposure and in-town per capita credit, as well as in-state per capita credit—all three variables and their cross interaction terms are included as well. Because including simultaneously all the subcomponents creates multicollinearity, IA Table A1.5 reports the marginal impact of drought exposure (and the corresponding p-value) for different points of the in-town and in-state credit distribution.

The marginal impact of the drought is consistent with the substitution-cum-migration hypothesis. Drought exposure implies a 3.47 (p-value=0.459) percentage point decline in population growth (1950-1960) for a town at the 10th percentile of per capita credit located next to in-state towns at the 10th percentile of per capita credit. But for the same drought-exposed town at the 10th percentile of the credit distribution, drought exposure implies a 6.53 (p-value=0.08) and a 10.7 (p-value=0.02) decline in population growth (1950-1960) respectively if the town is located next to in-state towns at the 50th and 90th percentiles of per capita credit respectively. Correspondingly, if the drought exposed town is itself a center of finance, then the negative effects of nearby in-state sources of credit is diminished: If the drought exposed town is at the 50th percentile of loans per capita, then the negative effect of in-state neighbors is smaller (6.3 percentage points) and only significant (p-value=0.09) if the neighbor is at the 90th percentile of credit. Likewise, if in-town credit at a drought exposed town is itself at the 90th percentile of loans per capita, then the negative effect of in-state neighbors even at the 90th percentile is now no longer economically or statistically significant.

Column 3 of Table 7 shows that a similar pattern emerges in the long run. The dependent variable is population growth over 1950-1980. From the marginal effects in IA Table A1.5, drought exposure suggests a 1.34 percentage point drop in population for a town at the 10th percentile of in-town per capita credit when in-state loans per capita in nearby towns is at the 10th percentile (p-value=0.03). This negative effect increases dramatically when nearby in-state neighbors are major centers of bank finance, and becomes small and insignificant when the drought exposed town is itself also a center of local finance.

Column 4 shows a similar effect for loan growth, using the change in loans between 1950 and 1960 among banks headquartered in a town, and scaled by total banking assets in 1950 as the dependent variable. From IA Table A1.5, which reports the marginal impact of the drought at different points of the joint in-state and in-town credit distribution (and associated p-values), there is dramatic evidence that lending almost collapses in drought exposed towns with relatively high credit constraints that are also located near relatively large in-state centers of bank finance.

Figure 2 illustrates this result. Loan growth among banks in a drought exposed town at the 10th percentile of loans per capita declines by about 77.5 percent when in-state loans per capita in nearby towns is at the 90th percentile (p-value<0.01). But for a drought exposed town at the median loans per capita also located near in-state towns at the 90th percentile, lending drops by only 26.1 percent (p-value<0.001); but if the drought exposed town is itself a center of finance—90th percentile of loans per capita—then being located near in-state towns at the 90th percentile has no significant impact on in-town bank-lending in response to the drought. To wit, nearby in-state banks become an important source of drought-adaptation bank credit when in-town potential credit supply is limited.

In sum, we have seen evidence that drought exposed towns and counties suffer significant emigration and demographic decline when credit availability is limited, creating long-run divergence. This result remains unchanged when including a large number of potentially confounding variables and using the plausibly exogenous variation in credit availability based on capital regulations set 40 years prior. We have also seen evidence that the adverse effects of drought exposure on demographic decline is particularly strong when both lending capacity within a town is limited and the lending capacity of neighboring in-state towns is relatively large.

No such result exists for neighboring out-of-state towns. The evidence suggests that bank finance helps local economies adapt to large scale environmental shocks.

4. Forms of Adaptation

We now turn to understand how credit helped influence adaptation. We start by examining investment in irrigation and in drought-resistant crops. Then we turn to automation, as well as, consequently, value and productivity. Finally we examine farm survival, ownership, and scale, as well as spillovers to other sectors.

4.1 Crop Adaptation, Irrigation and Capital Investment

Crop choice is an important dimension of drought adaptation, and since adopting new crops typically involves new seeds, new growing techniques, as well as a fair amount of risk, access to finance can help such adaptation. Sorghum is one such well-known drought resistant grain, and is often used to feed livestock instead of less-drought tolerant corn during times of drought (Abdel-Ghany, Ullah et al. 2020). Consistent with crop choice as an important adaptation margin, sorghum production significantly expanded across the US during the drought affected 1950s, rising from 12 to 27 million planted acres between 1952 and 1957 (Lin and Hoffman 1990). In part, this adaptation was driven by the development of new hybrid sorghum which was suitable for deficit irrigation, making it profitable for farmers to simultaneously invest in irrigation and shift production towards sorghum (Schertz 1979).

To gauge the importance of finance in this adaptation margin, column 1 of Table 8 studies the county-level variation in sorghum production—the change in the number of bushels between 1949 and 1959. Because farms are the decision making units, we would expect a bigger adaptation response in counties where farms have greater access to credit: where the ratio of ex-ante bank credit to the number of farms or the ratio of ex-ante bank credit to farm acreage in the county in 1950 is higher. We henceforth report results using both measures of credit, though for concision, the regression coefficient estimates are reported only for the first measure. In Panel A we report the marginal effects of drought exposure when using the ratio of bank credit to the number of farms as the measure of credit availability in the county, while in Panel B, we report the marginal effect of drought exposure when using the log of the ratio of bank credit to farm acreage in the county in 1950 as the measure of credit availability. From column 1, among drought exposed counties at the 10th percentile of the credit distribution, there is no significant change in sorghum production over this period. But at the 90th percentile of the credit distribution, sorghum production expands by about 19.03 percentage points (p-value=0.05). Note that these marginal affects are larger when credit access is measured at the acreage level (Panel B).

We next examine the role of credit availability in determining the overall investment and technological response to the drought. A farmer with access to credit will want to move away from rain-fed agriculture towards irrigated farming. Irrigation projects are also very capital intensive, making the irrigation response a particularly salient outcome variable to study the mediating role of access to finance. Importantly, as noted earlier, the center pivot irrigation system, patented in 1952, revolutionized American agriculture in the drier southwestern and western states, allowing farmers to access groundwater efficiently to farm in these more arid areas.[14]

The dependent variable in column 2 of Table 8 is the log change in irrigated farm acreage in a county between 1949 and 1959. The key variable of interest remains the top quartile drought indicator interacted with the stock of outstanding loans in 1950 divided by the number of farms in 1950. As always, the baseline specification also interacts the top quartile drought indicator variable with the log of the population in the county in 1950, as well as the log of the county area and includes all components of the interactions linearly along with state fixed effects. Drought exposed counties with access to credit significantly increased irrigated farm acreage during the 1950s. For a county at the 90th percentile of the per farm bank credit in 1950 distribution, drought exposure suggests a doubling of the irrigated farm acreage during the drought (p-value=0.01). But for a county at the 10th percentile of the bank credit distribution, drought exposure suggests a 64 percent decline in irrigated acreage (p-value=0.11), as surface water irrigation may have diminished on account of the drought and farmers in these more credit constrained counties lacked the external funds to adopt new ground-water irrigation technologies like the newly patented center-pivot systems.

These magnitudes imply *leapfrogging:* The investment in irrigation in drought exposed counties with access to credit not only exceeded that in drought exposed counties with limited access to credit, but it also exceeded even those counties that had similar access to credit but no

[14] Ground water irrigation, using modern versions of center pivot systems, remain the dominant form of agriculture in the southwest and western states https://pubs.usgs.gov/circ/1441/circ1441.pdf

drought. To see this, consider two counties at the 90th percentile of loans per farm. The predicted growth in acreage is about 3.64 percentage points in the drought exposed county. But with little reason to incur irrigation costs in the absence of a drought, the growth in irrigated acreage is only 2.68 percentage points in the non-drought exposed county—these differences are significant at the 10 percent level.

The dependent variable in column 3 is the log farm acres irrigated using ground water in 1959. Consistent with the shift away from rainfed agriculture, acres using ground water irrigation increased by 60 percent in 1959 among counties with top quartile drought exposure at the 90th percentile of the ex-ante loans per acre distribution. Again, these point estimates also imply leapfrogging: drought exposed counties with credit access expanded into ground water irrigation the most, as non-drought exposed areas would have had less incentive to adopt irrigation systems to access ground water even when credit access is plentiful (Figure 3). Consistent with these overall results, the log amount of water from all sources used in irrigation on farms in 1969—measured in terms of acres-feet—the earliest post-drought year with such data also declines (column 4) in drought exposed counties with limited access to credit. Nearly two decades after the drought began, counties exposed to the drought and at the 10th percentile of bank credit distribution had much lower irrigation water usage—a 58.6 percent lower (p-value=0.07).

While this evidence is suggestive that access to bank finance may have been key in helping drought-exposed areas transition to ground water-based irrigation agriculture, the 1950s and 1960s was a period of rapid and broad technological change. And census data observed at the decadal frequency can make it difficult to separate the role of credit supply in fostering this agricultural transition from that era's broader technological developments. To address this concern, we now turn to intra-year data on well-depth over the period 1950-1970 from the US Geological Survey to more precisely connect drought exposure, access to finance and the adoption of ground-water based irrigated farming.

The logic of these well-level tests is based on the fact that there is increased aquifer discharge in drought exposed areas when credit is used to finance a shift to ground-water irrigation through water mining. This depletion of the aquifer will in turn increase the depth of wells in the county—the distance from the earth's surface to the water-level in the well—as aquifer levels decline when water is mined to support ground-water based irrigation. However, in drought exposed areas with aquifers but limited access to finance, the inability to finance adaptation and the overall decline in agriculture will create less aquifer discharge, resulting in shallower well-depths.

The United States Geological Survey began collecting data on the water depth of about 106,000 wells across the United States, beginning in 1950.[15] These wells, dug for irrigation, commercial public water supply and monitoring uses provide information about the depth of local aquifers. On average each of these wells was sampled every 80 days during our 1950-1970 sample period, but some wells were sampled more frequently than others, so that the standard deviation of days between well-depth observations is about 252 days. Over the period 1950-1970, the summary statistics show that wells in drought exposed counties during the drought period (1950-1957) were about 30.75 feet deeper than wells not exposed to drought conditions (p-value<0.00). The mean well depth over the sample period was 57.6 feet with a standard deviation of 71.1 feet.

Column 1 of Table 9 examines the impact of drought exposure and bank credit access on well depth. The data are observed at the well-depth-observation date level and constitute an unbalanced panel over the sample period 1950-1970 that produce about 740,178 well-depth observations. This well-level panel structure allow us to include county fixed effects (because whether a county is in drought varies over time), absorbing local geographic and other time-invariant factors, such as the size of underlying aquifer. The basic specification includes an indicator variable that equals 1 if a well is located in a county-year pair that is in drought and 0 otherwise. This county-year drought indicator variable is also interacted with the 1950 loans per farm variable. This interaction term measures whether the effects of drought exposure on well's depth varies with credit availability in the county.

From column 1, the coefficient on the interaction term between the time-varying drought exposure variable and loans per capita in 1950 is positive and significant—well depths are deeper in drought exposed counties with more ex-ante credit access. For a county at the 10^{th} percentile of loans per farm variable, drought exposure implies a 17.7 feet decrease in the average well-depth in the county, as agriculture declined along with water usage. But for a county at the 90^{th} percentile of loans per farm, well depth increases by 16.4 feet—a difference of

[15] The data are obtained from https://waterservices.usgs.gov/rest/GW-Levels-Service.html. An overview of water monitoring and well-depth observations in the United States can be found here: https://cida.usgs.gov/ngwmn/doc/ngwmn_framework_report_july2013.pdf

about 34 feet from well depths for counties at the 10th percentile. Column 2 repeats this exercise using loans per acre. There is again evidence that wells become deeper as aquifers are mined to a greater extent in drought exposed counties with high ex-ante credit access. That is, drought exposure combined with access to finance facilitated a shift to ground water based irrigated agriculture in drought-exposed counties.

The US government did not observe well-depths before 1950 and we cannot formally test for differences in pre-drought trends across these counties. But the event study analysis in Figure 4 strikingly illustrates the post-drought well-depth dynamics across these counties, helping to connect causally the timing of drought exposure, credit and the shift towards ground-water irrigation. For each year of drought, the figure plots the average difference in well depth in counties at the 90th percentile of loans per farm to those at the 10th percentile (Panel A). This average difference is allowed to vary by year from 1950 through 1965—the first seven years of the drought in the sample period—1950-1957—and the seven years immediately after the drought ends—1958-1965. The overall sample period remains fixed at 1950-1970.

Using loans per farm as the measure of ex-ante credit access, well depth is on average about 45 feet deeper from 1950 to 1956—the peak drought years—in wells located in counties at the 90th percentile of bank finance relative to those at the 10th percentile. But once the drought ends circa 1957 and the rains recharge the aquifers, this gap shrinks rapidly to around zero, becoming insignificant by 1958. A similar pattern is observed when using loans per acre as the measure of ex-ante bank credit supply (Panel B). Together, this evidence suggests that farmers in counties with aquifers more easily adapted to the drought through water mining and ground-water irrigation in areas with more plentiful bank finance—see (Evett et al. 2020) for a survey of irrigation on the Great Plains.

We next examine the impact of the drought and credit access on other dimensions of farm capital investment, such as the adoption of trucks and tractors. As discussed earlier, many of these equipment are complements in the production process. For example, an increase in the scale of production because of irrigation can make it profitable for farmers to invest in additional tractors. Also a shift to ground water irrigation that reduces uncertainty over future water supply and profitability can make it optimal for farmers to increase capital investments, such as also using more tractors, heavy trucks and storage facilities to automate production and increase farm efficiency.

While the earliest post-drought year with data on trucks and autos as well as tractors is only 1969, the data are broken down separately for farms with cash flow less than \$2,500 (in 1969 dollars) and those with sales in excess of \$2,500. The former set of farms would likely be more dependent on external bank credit to finance any investment response to the drought. As IA Table A1.3 indicates, the mean number of tractors, and trucks and autos on farms with sales in excess of \$2,500 is respectively about 116 and 55 percent more than the mean number on farms with less than \$2,500 in sales.

The dependent variable in Table 10 column 1 is the mean number of trucks and cars on farms with sales less than \$2,500—about \$18,000 in 2022 dollars. Consistent with the prediction that credit availability is likely to matter more for the capital investment response of farms with low revenue, the mean number of trucks and autos on drought exposed counties at the 10th percentile of bank credit is about 3.7 percent (p-value=0.01) lower; but the impact of the drought on the number of trucks and autos in counties at the 90th percentile of the bank credit distribution is positive but not significant. In column 2, which uses the mean number of trucks and autos on farms with sales in excess of \$2,500, the bank credit-drought interaction term is not significant. That our measure of credit availability aligns well with the purchases of those who are likely to have had the highest demand for credit, is again suggestive that loans per capita is a good proxy for credit.

Columns 3 and 4 repeat this exercise using the mean number of tractors. Tractors are about three times more expensive than a typical truck, and usually require external financing. So we may expect more of an interaction effect here for higher revenue farms. For farms with sales less than \$2,500, the drought reduces the mean number of tractors by about 6.4 percent when bank credit is at the 10th percentile of the distribution (p-value<0.01). But at the 90th percentile of the credit distribution, the impact of the drought on the number of tractors is positive (2.9 percent) but not statistically significant (p-value=0.45). As in the case of autos, among farms with sales in excess of \$2,500 (column 4), the mediating role of credit is not statistically significant, except when credit availability is measured as loans per acre, when even high revenue farms have fewer tractors in areas with credit availability at the 10th percentile.

IA Table A1.6 studies whether drought adaptation through irrigation in counties with credit access complemented these physical investments farm equipment. To check for complementarities, the specification include a triple interaction term, interacting loans per farm, the drought indicator variable along with the log of acreage irrigated by ground water in 1959. All subcomponents of these interactions are also included in the regression, along with the standard log population and log area controls included linearly and interacted with the drought indicator variable.

IA Table A1.6 reports the marginal impact of drought exposure at different points of the credit distribution separately for whether the county is at the 10th or 90th percentile of ground water irrigation. At the 10th percentile of credit and irrigation, drought exposure suggests a 3.4 percent decline in the mean number of trucks and autos (p-value=0.03). But at the 90th percentile of credit and irrigation, drought exposure suggests a 9.2 percent increase in the mean number of trucks and autos (p-value=0.08). These marginal effects are much larger in the case of tractors (column 2). At the 10th percentiles of credit and irrigation, the mean number of tractors decline by about 6.4 percent in drought exposed counties (p-value=0.01). But for drought exposed counties at the 90th percentiles of credit and irrigation, the mean number of tractors increases by 14.9 percent (p-value<0.00). This suggests that drought exposure combined with ex-ante credit access may have been a catalyst for significant irrigation and other complementary investments.

4.3 The Pattern of Agricultural Ownership, Survival, and Growth

The ability to borrow and invest for survival, as well as for adaptation, would have allowed marginal farmers to survive. It would also have allowed larger farmers to grow farm size as they adopted complementary investments and increased the minimum scale of the land they needed. Some of this land may have come from credit-financed purchases from marginal farmers selling out, some of it may have come from new land purchased and brought into cultivation. Clearly, then, we have some unambiguous predictions. Tenant farmers, without land collateral, are usually the most marginal farmers, heavily dependent on cash flow. They are most likely to be able to benefit from greater access to finance during a drought.

So the dependent variable in Table 11 column 1 is the share of owner occupied farms in the county in 1959 (the rest are tenant occupied). The negative coefficient on the interaction suggests the tenant share is higher in counties with greater credit availability. Indeed, in a county at the 90th percentile, the tenant share is 2.3 percentage points higher (p=0.01) while it is not different from zero in a county at the 10th percentile. Interestingly, column 2 where the dependent variable is share owned in 1982 suggests the effect is persistent and even larger over time. Note that in all the columns in this table, we control for the lag of the dependent variable in

1950 to absorb the preexisting variation in these outcomes, as well as linearly for log population and area (in 1950) and interacted with the top quartile drought exposure.

In column 3, the dependent variable is the total acres in farming in 1959. It is about 14.3 percent higher (p-value=0.08) in drought exposed counties at the 90th percentile of ex-ante loans per farm distribution. Note that the marginal effects are qualitatively similar when using loans per acre in 1950 as the measure of credit access (Panel B), but often less precisely estimated. This effect seems to die away by 1982 (column 4).

Given that marginal farmers survive in greater numbers in the face of drought if buoyed by greater access to credit, we should see a higher number of farms at the end of the drought in 1959 in drought hit counties with greater credit availability. In column 5, the dependent variable is the number of farms in the county in 1959. The number of farms is about 7.6 percent (p-value<0.01) higher in counties at the 90th percentile of the credit distribution. Column 6 shows that by 1982, these positive effects are less precisely estimated.

IA Table A1.7 next examines the impact of the drought and credit availability on farm sizes. Since some farms grow with investment, while some marginal farmers also survive, the implications for average farm sizes are more ambiguous. Indeed, the effect of credit availability on mean farm size in 1959 in areas with greater access to credit is not statistically different from zero (column 1). However, by 1982, the effect of complementary investments seems to dominate (column 2). Mean farm size is 9.1% larger in counties at the 90th percentile of credit availability (p=0.04).

4.4 **Productivity**

We have seen that credit access helped farmers adapt better to the drought, and helped the local agricultural economy remain intact during the drought and afterwards. If credit access improved efficiency—better crop choices, new irrigation techniques and modern equipment—then productivity might increase relatively in drought exposed areas with good ex-ante credit access. Of course, if bank credit was poorly allocated during the drought, perhaps disproportionately going to well-connected local farmers, or keeping inefficient small farmers afloat, then there may be only slight differences in agricultural productivity across counties.

If land values reflect expected cash flow from agricultural production, then the mean value of farm land per farm in 1959 reasonably proxies for agricultural productivity.[16] This is the dependent variable in column 1 of Table 12. Column 1 shows that in 1959, soon after the drought ends, credit access and drought exposure do not significantly explain the variation in mean farm values. Perhaps the survival of small inefficient farms dampened the rise in land values associated with higher adaptation investment.

However, we have seen earlier that many of the complementary investments took time to build (David 1990). Column 2 shows that in the longer run, the variation in ex-ante credit access may have led to long-run divergence in agricultural productivity. The dependent variable in column 2 is the log mean value of land and buildings per farm in 1978. This variable is about 6.4 percent lower among drought exposed counties at the 10th percentile of the ex-ante credit distribution (p-value=0.08); at the 90th percentile of credit distribution, the marginal impact is positive (5.2 percent) but not significant (p-value=0.27). These differences are even bigger when credit access is measured on a per acre basis (Panel B), and point to a large spread in farm values on account of the drought depending on credit availability. This suggests that the relative lack of adaptation in counties with limited credit access during the drought years may have restrained long-run agricultural productivity.

Building on the evidence that adaptation through irrigation may have complemented capital investment and automation, column 3 examines whether adaptation through irrigation help explain these differences in long-run agricultural productivity. If drought exposed counties with access to credit adapted through irrigation, which in turn led farmers in these counties to adopt complementary farm equipment that enhance efficiency, then adaptation through irrigation could induce significant differences in long-run agricultural productivity.[17] Column 3 thus interacts loans per farm with the drought exposure indicator variable along with the log acres-feet of water used in irrigation in the county in 1969; the regression includes all subcomponent terms, along with the other standard controls. [18]

[16] Note that the mean value per acre reflects endogenous selection effects, as only the most productive land might remain in production in drought affected counties with limited credit access, while production might expand even to less fertile lands in areas with more credit.

[17] Note that some drought exposed counties with access to credit may not have adapted to irrigation because of the lack of sufficient groundwater.

[18] Because value per farm might reflect pre-existing farm size differences, as a robustness exercise, we have also re-estimated column 3 controlling for 1950 farm size using a similar triple interaction term between initial mean farm

The triple interaction term is positive and significant, suggesting that drought exposure combined with adaptation through irrigation and credit access can induce differences in long-run productivity. Figure 5 illustrates the relationship estimated in column 3. Using the estimates in column 3, the figure shows the relationship between the predicted log mean value of land and buildings per farm in 1978 and loans per farm in 1950 for drought and non-drought exposed counties at the 10^{th} and 90^{th} percentile of water used in irrigation in 1969.

Figure 5 shows two notable facts. First, credit has a positive effect on farm values only in the case of drought exposed counties that adapted through irrigation. This positive relationship reflects the ability of farmers in these counties to access credit in order to undertake the additional capital investment and automation that complement their adaptation towards irrigated agriculture. In turn, these complementary adaptation margins led to more productive and valuable farms in the long run. For example, among drought-exposed farms at the 90^{th} percentile of irrigation, mean farm values are about 23 percent higher when credit is at the 90th versus 10^{th} percentiles.

The second notable fact is that farm values is highest among drought exposed counties that adapted through irrigation (90^{th} percentile of water usage) when loans per farm at the 90^{th} percentile. Among this top group, values are some 8 percent higher than otherwise similar counties that never experienced a drought; 35 percent higher than drought exposed counties that did not adapt through irrigation (water usage at the 10^{th} percentile) and 38 percent higher than the low irrigation water counties that never experienced a drought. Column 4 repeats this exercise with the log acreage irrigated using ground water in 1959. The triple interaction term is also significant, and the pattern of results is similar. Together then, this evidence suggests that in the face of an adverse productivity shock, credit access that can facilitate complementary adaptation can induce long-run divergence in productivity.

4.5 Spillovers: Drought, credit and the non-agricultural economy

Unaddressed, the effects of drought can clearly spill over onto other facets of the local economy. This subsection examines the role of credit access in influencing the impact of the drought on the retail and manufacturing sectors. Easier access to credit can have both a direct and an indirect effect on the survival of non-tradeable businesses, such as local retail

size (1950), drought exposure and irrigation. The coefficient on the triple interaction between credit, drought and irrigation declines slightly to 0.067 (p-value=0.08).

establishments, during the drought. For a given decline in local demand on account of the drought, the non-tradeable sector might access working capital and fulfil its other credit needs in areas with high ex-ante credit availability, helping the sector survive. By helping farmers and other businesses survive, and by limiting population shrinkage, credit can also preserve local demand in the face of the drought, indirectly benefitting the non-tradeable sector.

Table 13 studies the impact of the drought on the non-agricultural economy. Column 1 proxies for the size of the local non-tradeable sector using the log number of retail establishments in the county in 1967. We control for the initial pre-drought size of the retail sector using the log number of retail establishments in 1952—these are the two closest years with the data that are adjacent to the pre and post drought period. All specifications also include the baseline controls. Drought exposure is associated with a 9.2 percent decline in the number of retail establishments in 1967 in counties at the 10^{th} percentile of the credit distribution (p-value=0.11). The negative impact of drought exposure on retail growth in areas with limited credit is similar when measured over the 1952-1977 period, but is more precisely estimated (column 2). At the 10^{th} percentile of loans per farm for example, drought exposure suggests an 8.6 percent drop in the number of retail establishments (p-value=0.02).

The demand for manufacturing products is often national or international and is unlikely to be directly affected by the drought. Instead, droughts can affect the manufacturing sector mainly through the firm credit and the labor supply channel. In areas with limited access to credit, the contraction of the agricultural economy in response to the drought can push labor off farms and increase local labor supply, allowing the local manufacturing sector to expand. However, if low local farm credit availability also proxies for credit constraints in the manufacturing sector, then the capacity of the manufacturing sector to absorb surplus farm labor in the short run might also be limited. Then drought-induced net local outmigration could reduce potential labor supply over time, increase manufacturing labor costs, and hurt the manufacturing sector.

Columns 3 and 4 of Table 13 strongly suggests that drought exposure and limited credit access had negative spillover effects on the local manufacturing sector. The dependent variable in column 3 is the log number of manufacturing establishments in the county in 1967, and we control for the pre-existing size of the manufacturing base using the log number of manufacturing establishments in 1940. Column 3 suggests that at the 10^{th} percentile of loans per farm, drought exposure suggests an 11.4 percent drop in the number of manufacturing establishments (p-value=0.06). Column 4 shows that these effects widen over time. By 1977, the number of manufacturing establishments is about 15 percent lower in drought exposed counties at the 10th percentile of loans per farm in 1950. As Panels A, B and C show, these estimates are broadly similar when using either loans per farm, loans per acre or loans per capita as the proxy for ex-ante credit constraints.

5. Conclusion

We collect bank balance sheet data, along with economic and demographic data across US towns and counties, to study how credit availability can interact with climatic shocks to determine long run economic outcomes. We find that exposure to the drought leads to large and persistent declines in population at both the town and county-levels, in part driven by emigration. However, ex-ante credit availability moderates the demographic and economic impact of the drought, especially when internal cash flow and self-financing is limited. Notably, smaller farms in drought exposed towns actually increase investment in new technologies when credit is available. A similar pattern emerges at the county level. We also find that adaptation takes time. And in the longer run, agriculture in drought exposed counties with access to finance, and the physical means to adapt through ground water, become more productive than areas never touched by the drought.

These results are supportive of the importance of funding for adaptation investment in enabling communities to survive climatic calamities – an issue that rightly concerns poorer countries as they face climate change. To the extent that it helps unaffected communities avoid waves of uncontrolled climate-induced immigration, these communities too have an interest in providing that financing. Indeed, our paper suggests that with adequate financing, and the physical means to adapt, say through groundwater usage, climate-hit communities may even bring forward investment that would otherwise take place with delay, allowing them to build future buffers and even incomes. Conversely, we also find that inequality in access to finance can actually exacerbate outmigration, from finance-poor communities to finance-rich communities. So broadening access to finance may be really important to ensure the bulk of the change takes place through local adaptation rather than migration, as we face up to the challenge of climate change.

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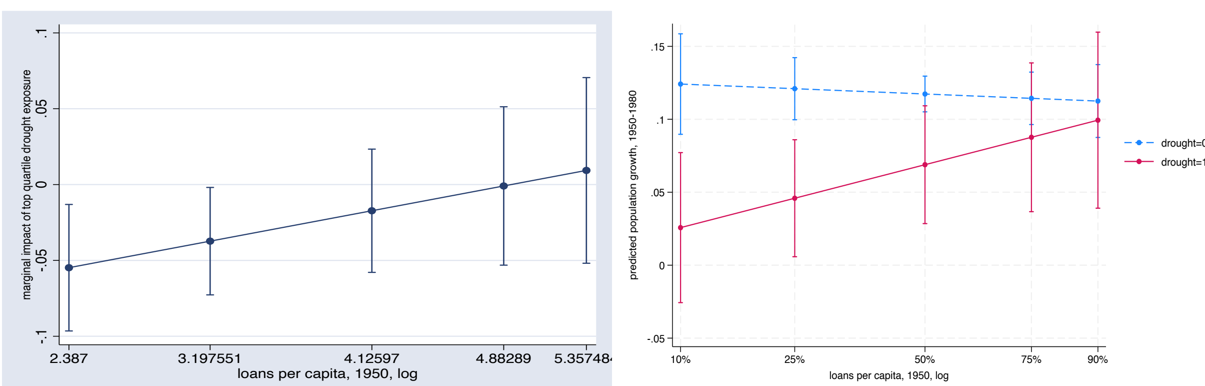
Figures and Tables

Figure 1 The marginal impact of top quartile drought exposure on county-level population growth, 1950-1960, as a function of loans per capita, 1950, log

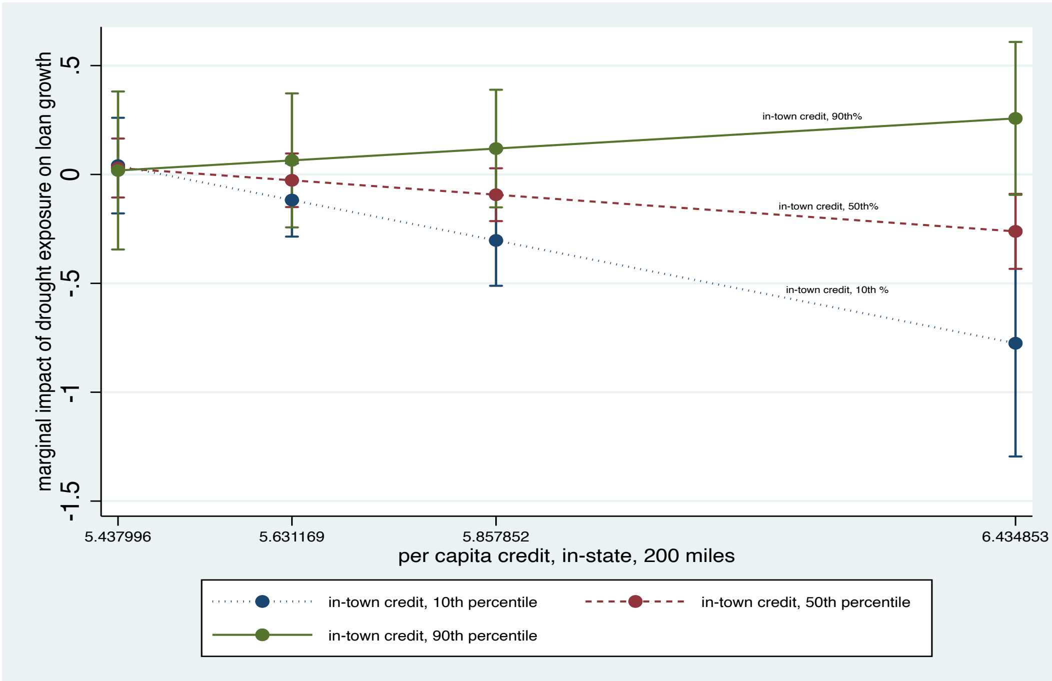
Panel A. Marginal effect of top quartile drought 1950-1960

Panel B. Predicted population growth, 1950- 1980.



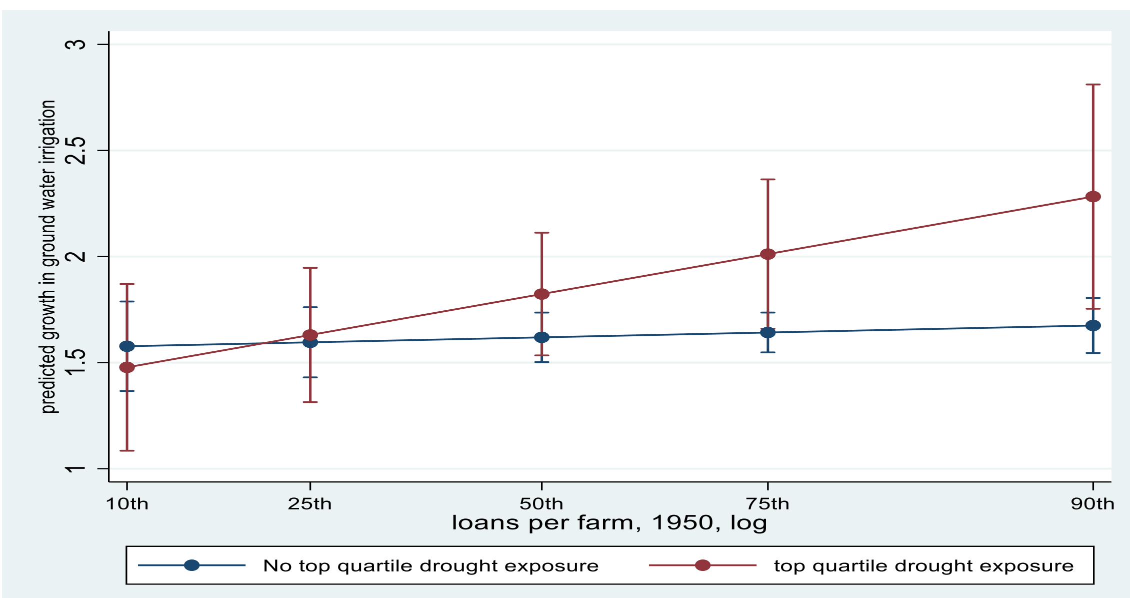
Notes: Panel A plots the marginal impact of top quartile drought exposure as estimated in Table 3, column 4. Panel B plots the predicted population growth between 1950-1980 from the model estimated in column 7 of Table 3. The blue line predicts population growth for counties not exposed to top quartile drought intensity at the 10th, 25th, 50th, 75th and 90th percentiles of the loans per capita, 1950, log distribution. The red line repeats this exercise but for counties that are exposed to top quartile drought intensity.

Figure 2 The marginal impact of drought exposure on loan growth, 1950-1960



This figure uses the coefficients from column 4 of Table 7 to plot the marginal impact of drought exposure on loan growth as a function of in-state per capita credit. These marginal effects are evaluated separately for towns at the 10th 50th and 90th percentiles of in-town loans per capita .

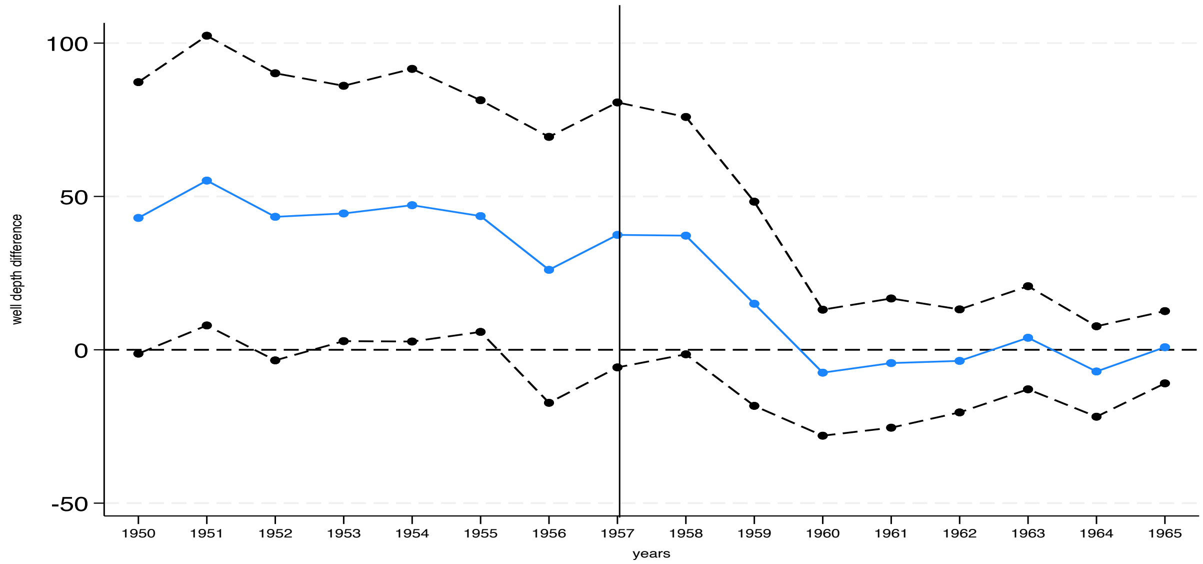
Figure 3 Predicted land acreage irrigated by ground water sources on farm, 1959



Using the model estimated in column 3 of Table 8, this figure plots the predicted growth in the irrigated acreage over 1949-1959 over the distribution of loans per farm, 1950, separately for drought exposed and non-drought exposed counties.

Figure 4. The difference in well-depth between counties at the 90th and 10th percentiles of credit, 1950-1965

Panel A. Loans Per Farm

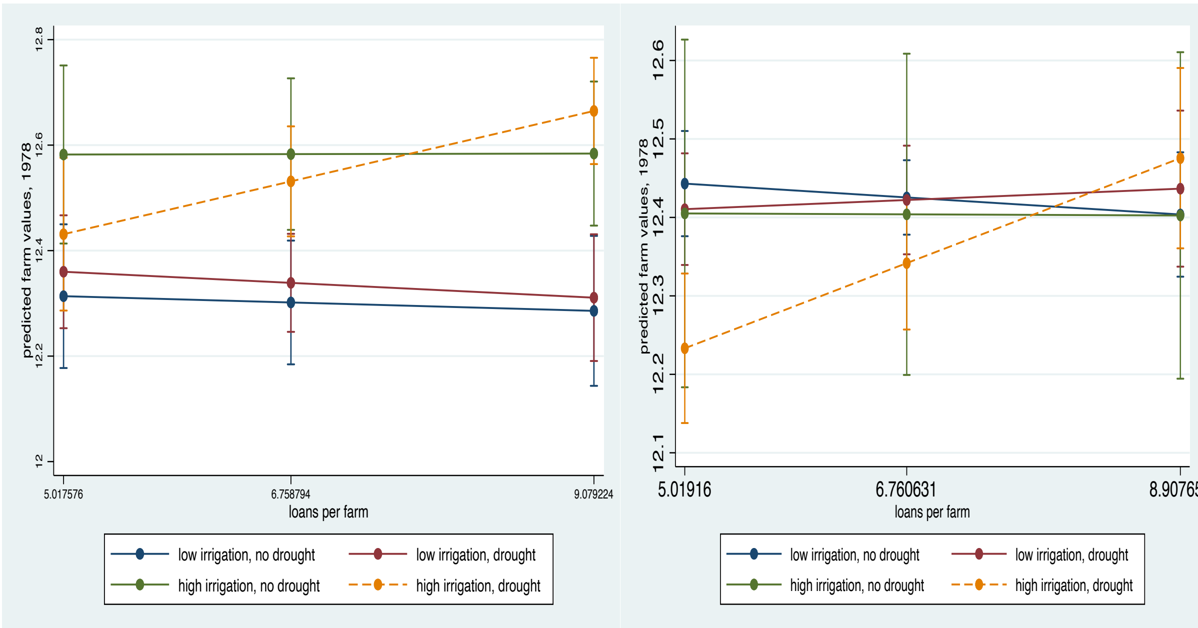


Panel B. Loans Per Acre

These figures plot the coefficients—solid line—along with the 95% confidence bands—dashed lines—for the average difference in well depth in each year between a county at the 90th percentile of bank credit (loans per farm or loans per acre) and a county at the 10th percentile of bank credit. The regression includes county-fixed effects and standard errors are clustered at the county-level. The sample period is 1950-1970, the dependent variable is well depth (in feet) observed on a given date, and the dataset consists of an unbalanced panel of about 106,000 wells. The drought began circa 1949 and ended circa 1957.

Figure 5. Long-Run Agricultural Productivity, and Adaptation Through Irrigation

Panel A. Log acres-feet of water used in irrigation, 1969. Panel B. Log acreage irrigated using groundwater, 1959



Panel A and B use the point estimates from columns 3 and 4 of Table 12 respectively to compute the predicted log mean farm value in 1978. "Low irrigation, no drought" shows the impact of loans per farm on predicted mean farm value for counties at the 10th percentile of irrigated water usage in 1969 and no top quartile drought exposure. "Low irrigation, drought" shows the impact of loans per farm on predicted mean farm value for counties at the 10th percentile of irrigated water usage in 1969 and top quartile drought exposure. "high irrigation, no drought" shows the impact of loans per farm on predicted mean farm value for counties at the 90th percentile of irrigated water usage in 1969 and no top quartile drought exposure. "high irrigation, drought" shows the impact of loans per farm on predicted mean farm value for counties at the 10th percentile of irrigated water usage in 1969 and top quartile drought exposure. Panel B measures irrigation using the "acreage irrigated by ground water sources in a county in 1959" Panel A measures irrigation using the log acres-feet of water used in irrigation (from all sources) in a county in 1969.

Tables

Table 1. Summary statistics: Bank credit availability, 1950

	Loans per capita	Number of banks per 10,000 people	Population
	County-level		
Mean	115.04	7.02	85,614
Std.dev	333.72	7.16	259,896
	Town-level		
Mean	615.91	8.16	29,093
Std.dev	2733.98	10.49	159,068

This table reports summary statistics across 1,263 towns in 1950 and among the 990 counties in which these towns are located. The underlying data is hand-collected bank balance sheet information for each bank in the sample of towns—about 3,015 banks in total. Note that overall data collection includes 5,621 banks in 1929; 2,985 banks in 1939; 3,027 banks in 1960 and 4,148 banks in 1970.

Table 2. Ex-Ante Credit and Population Outcomes at the County-Level (1950) and Drought Exposure (1950-1960)

	(1) loans per capita	(2) banks per 10,000 persons	(3) log population, 1950	(4) loans per capita	(5) banks per 10,000 persons	(6) log population, 1950
4th quartile drought intensity, 1950-1960	0.0591	0.00240	-0.0173			
	(0.113)	(0.0498)	(0.0165)			
std dev of land area in drought, 1895-1926				-0.0169	-0.000465	-0.000391
				(0.0412)	(0.0130)	(0.00491)
mean of land area in drought, 1895-1926				-0.0141	0.000304	-0.00458
				(0.104)	(0.0252)	(0.0133)
N	993	993	993	993	993	993
adj. R^2	0.076	0.502	0.357	0.077	0.502	0.356

Columns 1-3 examine the impact of top quartile drought exposure on ex-ante credit and population outcomes; columns 4-6 repeat this exercise for previous (1895-1926) drought outcomes. All regressions include state fixed effects and standard errors are clustered at the state-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 The impact of drought exposure on population growth—county-level evidence

	(1) all counties	(2) in-sample	(3) non-linear	(4) baseline	(5) WLS	(6) controls	(7) 1950-1980
drought intensity, 1950-1960, SPI continuous measure	-0.00528**	-0.00773*					
	(0.00235)	(0.00430)					
2nd quartile drought intensity, 1950-1960			-0.0133				
			(0.0256)				
3rd quartile drought intensity, 1950-1960			-0.0368				
			(0.0276)				
4th quartile drought intensity, 1950-1960			-0.0661**	-0.645**	-1.142***	1.070	-0.920**
			(0.0317)	(0.290)	(0.341)	(0.864)	(0.415)
log loans per capita, 1950				-0.000867	-0.0291**	-0.00418	-0.00459
				(0.00582)	(0.0111)	(0.00370)	(0.00889)
4th quartile drought intensity*loans per capita				0.0274**	0.0423**	0.0176*	0.0316**
				(0.0124)	(0.0160)	(0.00909)	(0.0152)
log population, 1950				0.0748***	0.0128	0.0180	0.107***
				(0.00989)	(0.00868)	(0.0141)	(0.0168)
4th quartile drought intensity*population				0.0188	0.0752***	0.0521**	0.0416**
				(0.0135)	(0.0160)	(0.0219)	(0.0201)
log, area				-0.0129	0.0469**	0.0105	-0.0248
				(0.0184)	(0.0174)	(0.0176)	(0.0314)
4th quartile drought intensity*area				0.0438	0.0122	-0.0231	0.0418
				(0.0278)	(0.0418)	(0.0306)	(0.0443)
N	3082	993	993	991	991	989	991
adj. R^2	0.194	0.205	0.206	0.330	0.381	0.463	0.344
The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per capita, 1950, distribution:							
10th percentile				-0.0630	-0.0123	-0.0404	-0.103
p-val				0.00343	0.697	0.0153	0.00279
50th percentile				-0.0153	0.0615	-0.00971	-0.0481
p-val				0.410	0.0859	0.340	0.0677
90th percentile				0.0183	0.113	0.0118	-0.00944
p-val				0.534	0.0233	0.495	0.788

Notes: This table examines the impact of drought exposure on the log change in population in the sample of counties. The dependent variable in columns 1-6 is the log change in population between 1950-1960; the dependent variable in column 7 is the log change in population between 1950-1980. All regressions include state fixed effects, and linearly include the log population in 1950 and log county area in 1950, as well as interacted with the top quartile drought indicator variable. Standard errors in parentheses and are clustered at the state level * p < 0.10, ** p < 0.05, *** p < 0.01. Column 6 interacts the drought indicator variable (4th quartile drought intensity, 1950-1960) with deposits per capita, 1950, the mean rainfall in the county; the standard deviation of rainfall; mean snow fall; the standard deviation of snowfall (all based on 20th century averages); the log of county area; the log of median income in the county in 1950; the share of rural population in 1950. In all columns except 7, the mean of the dependent variable is 0.064 and the standard deviation is 0.21; in column 7 the mean of the dependent variable is 0.10 and the standard deviation is 0.32. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 The impact of drought exposure on demographic outcomes—county-level evidence

Vital Statistics

	(1) migration	(2) births per capita, 1960	(3) births per capita, 1980	(4) deaths per capita, 1960	(5) deaths per capita, 1980
4th quartile drought intensity, 1950-1960	-14.78** (6.266)	-0.230 (0.141)	-0.221 (0.184)	0.572*** (0.187)	0.612*** (0.163)
log loans per capita, 1950	-0.177 (0.250)	-0.000497 (0.00322)	0.00479 (0.00364)	-0.00254 (0.00378)	0.00124 (0.00561)
4th quartile drought intensity*loans per capita	0.799** (0.369)	0.0152* (0.00787)	0.00809 (0.00638)	-0.00520 (0.00832)	-0.0193* (0.0110)
N	988	988	988	988	988
adj. R^2	0.302	0.579	0.452	0.584	0.346
mean	16.66	-3.788	-4.130	-4.617	-4.617
sdev	7.470	0.161	0.159	0.215	0.215
The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per capita distribution:					
10th percentile	-1.666	-0.0313	0.00334	0.0294	0.0871
p-val	0.0430	0.0269	0.803	0.112	0.00125
50th percentile	-0.239	-0.00415	0.0178	0.0201	0.0525
p-val	0.689	0.729	0.0662	0.132	0.0197
90th percentile	0.750	0.0147	0.0278	0.0137	0.0286
p-val	0.365	0.433	0.0447	0.449	0.321

Notes: This table examines the impact of drought exposure on migration, births and deaths. All regressions include state fixed effects, and linearly include the log population in 1950 and county area (log), as well as interacted with the top quartile drought indicator variable. Standard errors in parentheses and are clustered at the state level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "Migration, 1960" is the percent of the population within a county in 1960 that emigrated from another county in the previous decade. The mean and standard deviation of this variable is 16.65 and 7.47 respectively. The marginal effect of top quartile drought exposure is always evaluated at the mean of the other covariates.

Table 5. The impact of drought exposure on town-level credit growth

	(1) loan growth, 1950-1960	(2) loan growth, 1940-1950	(3) loans to assets,1960	(4) loans to assets,1960
4th quartile drought intensity, 1950-1960	-1.374*	-0.147	-0.299***	-0.302***
	(0.727)	(0.110)	(0.0872)	(0.0874)
log loans per capita, 1950	-0.291**		0.0321***	0.0331***
	(0.118)		(0.00570)	(0.00522)
4th quartile drought intensity*loans per capita 1950	0.221**		0.0462***	0.0458***
	(0.102)		(0.0107)	(0.0106)
log loans per capita, 1939		-0.0106		
		(0.00705)		
4th quartile drought intensity*loans per capita, 1939		0.0042		
		(0.1161)		
N	1309	1290	1230	1230
adj. R^2	0.081	0.043	0.259	0.262
The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per capita distribution:				
10th percentile	-0.306	0.00601	-0.0478	-0.0433
p-val	0.00736	0.699	0.00859	0.0207
50th percentile	-0.0847	0.0105	-0.00235	0.00177
p-val	0.163	0.252	0.800	0.862
90th percentile	0.145	0.0140	0.0455	0.0492
p-val	0.277	0.279	0.000	0.000

This table examines the impact of drought exposure on credit outcomes in the sample of towns. Loan growth is defined as the change in the stock of loans between two time periods divided by bank assets in the initial time period. All regressions linearly include log population in the beginning decade, and log population is also interacted with the drought indicator variable; all regressions also include state-fixed effects and standard errors, in parentheses, are clustered at the state-level. Column 4 includes the change in deposits (scaled by assets) and the change in bank capital (scaled by assets) both linearly and interacted with the drought indicator variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 The impact of drought exposure on town-level outcomes, control function approach

VARIABLES	(1) credit growth 1950-1960	(2) population growth 1950-1960	(3) 1950-1980
4th quartile drought intensity, 1950-1960	-1.299**	-0.761***	-1.641***
	(0.637)	(0.200)	(0.434)
loans per capita, 1950, log	0.00557	-0.0346	0.176
	(0.324)	(0.152)	(0.209)
4th quartile drought intensity#loans per capita, 1950, log	0.199**	0.0756**	0.166**
	(0.0949)	(0.0318)	(0.0650)
Control function, based on 1910 capital requirement	-0.230	0.0659	-0.137
	(0.328)	(0.153)	(0.217)
Observations	1,177	1,170	1,060
R-squared	0.098	0.109	0.172
p-value	0.483	0.668	0.526

Notes: This table studies the impact of drought exposure on town-level outcomes. Columns 1-3 includes the residual from regressing the log of loans per capita in 1950 on the log 1910 capital requirement along with the drought exposure indicator variable, the log population in 1950, and the interaction between these two variables, as well as state fixed effects—the first stage regression. The coefficient on the log 1910 capital requirement is 0.295 with an F-statistic of 7.22 (p-value=0.01). Credit growth is defined as the change in the stock of loans between 1950 and 1960 divided by bank assets in 1950. All regressions include the log population in 1950 both linearly and interacted with the drought indicator variable. Standard errors, in parentheses, are bootstrapped and clustered at the state-level. ***,**,* denote statistical significance at the 10, 5 and 1 percent respectively. The "p-value" reports the significance of the control function residual.

Table 7. The impact of drought exposure and state borders discontinuities

	(1) population growth, 1950-1960	(2) population growth, 1950-1960	(3) population growth, 1950-1980	(4) loan growth, 1950-1960
4th quartile drought intensity, 1950-1960	0.0487	-1.430	6.830	18.97**
	(0.480)	(1.903)	(6.693)	(8.662)
loans per capita, 1950, log, **in-town**	0.0337**	0.130	0.256	1.409
	(0.0161)	(0.0827)	(0.184)	(1.665)
4th quartile drought intensity,#loans per capita, 1950, log, **in-town**	0.0652**	0.320	-1.129	-2.905*
	(0.0296)	(0.326)	(1.181)	(1.447)
loans per capita, 1950, log, **in-state**	-0.0464	0.0583	0.165	1.875
	(0.0325)	(0.0676)	(0.166)	(1.943)
4th quartile drought intensity,#loans per capita, 1950, log, **in-state**	-0.0893**	0.159	-1.316	-3.423**
	(0.0397)	(0.311)	(1.187)	(1.530)
loans per capita, 1950, log, **out-of-state**	-0.0211*	-0.0226*	0.00485	0.0319
	(0.0123)	(0.0120)	(0.0395)	(0.119)
4th quartile drought intensity,# loans per capita, 1950, log, **out-of-state**	-0.0181	-0.0121	-0.100	-0.134
	(0.0334)	(0.0336)	(0.0968)	(0.107)
4th quartile drought intensity,#loans per capita, **in-town**, log#loans per capita, 1950, log, **in-state**		-0.0432	0.213	0.535**
		(0.0524)	(0.208)	(0.253)
N	1213	1213	1098	1219
adj. R^2	0.102	0.102	0.155	0.102

This table studies the impact of in-state and out-of-state sources of bank finance on town-level outcomes. ,In-state loans per capita, 1950, is the loans per capita computed over towns up to 200 miles from the reference town and located in the same state. The "out-of-state" counterpart is identical except this variable is computed among towns located across state-lines from the reference town. All regressions linearly include the town's population (log), as well as the sum of the population among nearby towns (in the same distance window) in state, as well as out-of-state. All population variables are interacted with the drought exposure variable. Columns 2-4 include all the subcomponents of the interaction terms. All regressions also include state-fixed effects and standard errors, in parentheses, are clustered at the state-level. ***,**,* denote statistical significance at the 10, 5 and 1 percent respectively.

Table 8. Investment and Technological Adaptation: Irrigation

	(1) change in sorghum production, 1949-1959	(2) growth in irrigated acres: 1949-1959	(3) log of groundwater irrigated acres,1959	(4) irrigation water usage, 1969
4th quartile drought intensity, 1950-1960	-0.288	0.441	1.674	2.767
	(0.706)	(4.492)	(2.853)	(3.016)
log loans per farm 1950	-0.0515	-0.280***	0.0241	-0.106
	(0.0317)	(0.0608)	(0.0351)	(0.0666)
4th quartile drought intensity*loans per farm	0.0288	0.401**	0.172*	0.259*
	(0.0322)	(0.150)	(0.0950)	(0.148)
N	590	969	968	928
adj. R^2	0.506	0.364	0.863	0.630
mean		3.311	1.717	5.601
stdev		2.613	3.357	3.239
Panel A. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:				
10th percentile	0.0872	-0.639	-0.0964	-0.602
p-val	0.253	0.110	0.723	0.0690
50th percentile	0.136	0.0593	0.203	-0.148
p-val	0.0367	0.820	0.321	0.545
90th percentile	0.190	0.988	0.601	0.463
p-val	0.0538	0.0126	0.0381	0.319
Panel B. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per acre distribution:				
10th percentile	0.0426	-0.828	-0.133	-0.677
p-val	0.594	0.0451	0.659	0.0755
50th percentile	0.130	0.0689	0.211	-0.135
p-val	0.0373	0.794	0.309	0.577
90th percentile	0.234	1.174	0.636	0.542
p-val	0.0744	0.00411	0.0657	0.359

Notes: This table studies the impact of drought exposure on county-level irrigation outcomes and sorghum production. All regressions include the log population in 1950 and log area in 1950 both linearly and interacted with the drought indicator variable along with state fixed effects; column 2 also includes the log irrigated acres in 1949. Panel A reports the marginal effect of drought exposure at different points in the log loans per capita distribution. We re-estimate all regressions using the log loans per acre as the measure of ex-ante credit access. Panel B reports the marginal effects from these regressions. All regressions also include state fixed effects. Standard errors, in parentheses, are clustered at the state-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Investment and Technological Adaptation: The Depth of Water-Wells

	(1) well-depth	(2) well-depth
drought exposure	-49.70***	-13.66***
	(13.54)	(3.298)
drought exposure*loans per farm	6.223***	
	(1.944)	
drought exposure*loans per acres		5.050***
		(1.122)
N	740178	740178
adj. R^2	0.484	0.485
The marginal effect of drought exposure, evaluated at the 10th, 50th and 90th percentile of the bank credit distribution		
10th percentile	-17.71	-16.55
p-val	0.00	0.00
50th percentile	-5.107	-3.660
p-val	0.08	0.23
90th percentile	16.45	16.99
p-val	0.03	0.01

Notes: This table studies the impact of drought exposure and credit access on the depth of about 106,000 wells observed as an unbalanced panel between 1950-1970. Well-depth measures the depletion of the local aquifer. The drought began circa 1949 and ended circa 1957. The dependent variable is the depth of a well in feet. The bottom panel reports the marginal effect of drought exposure at different points in the loans per farm (column 1) and loans per acre (column 2) distribution. All regressions include county-fixed effects, and standard errors are clustered at the county-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Investment and Technological Adaptation: Capital Equipment Investment, 1969

	(1)	(2)	(3)	(4)
	mean trucks and cars		mean tractors	
	Low turnover farms.	High turnover farms	Low turnover farms.	High turnover farms
4th quartile drought intensity, 1950-1960	-0.306*	-0.158	0.0404	-0.0895
	(0.181)	(0.230)	(0.334)	(0.436)
log loans per farm 1950	-0.00166	0.00642	-0.00940	-0.00479
	(0.00377)	(0.00478)	(0.00591)	(0.00850)
4th quartile drought intensity*loans per farm	0.0176**	0.00726	0.0242**	0.0153
	(0.00734)	(0.00854)	(0.0104)	(0.0126)
N	931	932	931	932
adj. R^2	0.439	0.558	0.592	0.491
Panel A. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:				
10th percentile	-0.0372	0.00108	-0.0640	-0.0498
p-val	0.0102	0.943	0.00417	0.129
50th percentile	-0.00673	0.0137	-0.0221	-0.0233
p-val	0.669	0.417	0.329	0.401
90th percentile	0.0306	0.0291	0.0291	0.00921
p-val	0.271	0.348	0.451	0.824
Panel B. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:				
10th percentile	-0.0398	0.000626	-0.0708	-0.0604
p-val	0.00862	0.967	0.00187	0.0754
50th percentile	-0.00648	0.0133	-0.0215	-0.0230
p-val	0.691	0.447	0.362	0.418
90th percentile	0.0335	0.0285	0.0375	0.0220
p-val	0.291	0.435	0.413	0.680

Notes: This table studies the impact of drought exposure on county-level capital investment outcomes. The Agricultural Census reports these data separately for low turnover farms: annual sales less than $2,500,about $18,000 in 2022 dollars, and high turnover farms sales in excess of $2,500. We re-estimate all regressions using the log loans per acres as the measure of ex-ante credit access. Panel B reports the marginal effects from these regressions. All regressions also include state fixed effects and log population and area in 1950 both linearly and interacted with the drought indicator variable;. Standard errors, in parentheses, are clustered at the state-level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 11. The Pattern of Agricultural Production A. Ownership, Acreage and Number

	(1) farm ownership, 1959	(2) farm ownership, 1982	(3) farm acreage, 1959	(4) farm acreage, 1982	(5) # farms, 1959	(6) # farms, 1982
4th quartile drought intensity, 1950-1960	-0.0427	-0.0504	-0.0352	0.139	-0.562**	-1.146**
	(0.0638)	(0.123)	(0.169)	(0.361)	(0.234)	(0.561)
log loans per farm 1950	-0.00323*	-0.000440	-0.00813	0.00664	0.00131	0.00869
	(0.00178)	(0.00283)	(0.00859)	(0.0120)	(0.00461)	(0.0129)
4th quartile drought intensity*loans per farm	-0.00741**	-0.0132**	0.0442	0.00852	0.0221***	0.0245*
	(0.00281)	(0.00599)	(0.0270)	(0.0159)	(0.00697)	(0.0143)
N	979	977	981	978	983	982
adj. R^2	0.945	0.783	0.970	0.929	0.948	0.800
mean	0.558	0.563	5.579	5.322	7.152	6.589
stdev	0.182	0.142	0.850	1.046	0.687	0.783
Panel A. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:						
10th percentile	0.00681	0.0142	-0.0300	0.0331	-0.0128	-0.00895
p-val	0.305	0.192	0.292	0.299	0.492	0.814
50th percentile	-0.00626	-0.00890	0.0474	0.0481	0.0258	0.0339
p-val	0.170	0.328	0.0758	0.0947	0.132	0.358
90th percentile	-0.0233	-0.0371	0.144	0.0663	0.0765	0.0890
p-val	0.00578	0.0505	0.0880	0.204	0.00484	0.115
Panel B. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per acre distribution:						
10th percentile	0.00446	0.0118	-0.0630	0.0335	-0.0258	-0.0415
p-val	0.499	0.275	0.289	0.305	0.218	0.314
50th percentile	-0.00653	-0.00948	0.0501	0.0485	0.0275	0.0367
p-val	0.200	0.337	0.0782	0.100	0.126	0.333
90th percentile	-0.0199	-0.0347	0.187	0.0662	0.0926	0.132
p-val	0.0472	0.113	0.139	0.297	0.00317	0.0422

Notes: This table studies the impact of drought exposure on the farm size distribution. We re-estimate all regressions using the log loans per acre as the measure of ex-ante credit access. Panel B reports the marginal effects from these regressions. All regressions also include state fixed effects and log population and area in 1950 both linearly and interacted with the drought indicator variable; all regressions include the lag (1950) of the dependent variable. Standard errors, in parentheses, are clustered at the state-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Productivity and Income

	(1) log mean value per farm, 1959	(2) log mean value per farm, 1978	(3) log mean value per farm, 1978	(4) log mean value per farm, 1978
4th quartile drought intensity, 1950-1960	-0.351 (0.439)	-0.199 (0.668)	-0.00711 (0.752)	-0.183 (0.669)
log loans per farm 1950	0.0263^{**} (0.00996)	-0.00774 (0.0132)	0.00615 (0.0193)	-0.0101 (0.0141)
4th quartile drought intensity*loans per farm	0.00438 (0.0156)	0.0300^{*} (0.0157)	-0.0276 (0.0264)	0.0168 (0.0182)
4th quartile drought intensity*loans per farm*log irrigation water usage			0.00836^{**} (0.00337)	
4th quartile drought intensity*loans per farm*log ground water irrigation usage				0.00577^{**} (0.00243)
N	983	982	928	981
adj. R^2	0.908	0.765	0.765	0.765
mean	10.31	12.41		
stdev	0.734	0.601		
Panel A. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:				
10th percentile	-0.0236	-0.0645		
p-val	0.516	0.08		
50th percentile	-0.0160	-0.0122		
p-val	0.470	0.722		
90th percentile	-0.00658	0.0521		
p-val	0.866	0.274		
Panel B. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per acre distribution:				
10th percentile	-0.0362	-0.0595		
p-val	0.358	0.123		
50th percentile	-0.0146	0.000123		
p-val	0.517	0.996		
90th percentile	0.0111	0.0709		
p-val	0.824	0.05		

Notes: This table studies the impact of drought exposure on county-level measures of farm productivity (mean value of farm land and buildings per farm and income). We re-estimate all regressions using the log loans per acre as the measure of ex-ante credit access. Panel B reports the marginal effects from these regressions. All regressions include the log population in 1950 and county area both linearly and interacted with the drought indicator variable; all regressions also include state fixed effects and the log of mean farm values in 1949. Column 3 includes a triple interaction term that includes the log of irrigated water usage on farms in 1969 (acres-feet) along with all subcomponents. Column 4 includes a triple interaction term that includes the log of irrigated acreage on farms in 1959 that uses ground water irrigation along with all subcomponents. The predicted values from the regressions in columns 3 and 4 are shown Figure 5.

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Table 13 Drought, credit and the non-agricultural economy

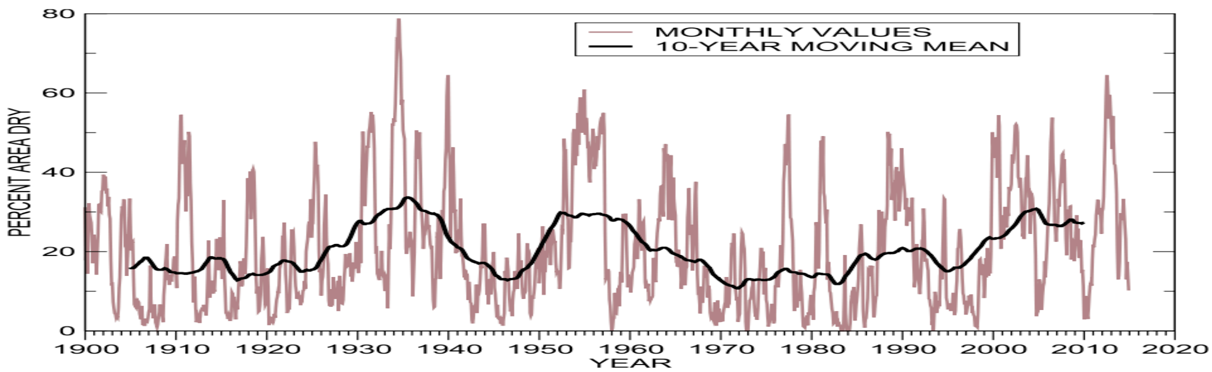
	(1) retail establisments, 1967	(2) retail establisments, 1977	(3) manufacturing establishments, 1963	(4) manufacturing establishments, 1977
4th quartile drought intensity, 1950-1960	-0.664	-0.912*	-0.251	-0.326
	(0.501)	(0.480)	(0.619)	(0.835)
log loans per farm 1950	0.00918	-0.00651	0.0123	-0.00227
	(0.00947)	(0.0105)	(0.00989)	(0.0112)
4th quartile drought intensity*loans per farm	0.0420*	0.0321	0.0189	0.0453*
	(0.0234)	(0.0207)	(0.0218)	(0.0253)
N	977	987	987	987
adj. R^2	0.746	0.942	0.935	0.896
mean	4.431	5.997	3.879	201.4
stdev	0.561	1.184	1.370	860.9
Panel A. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:				
10th percentile	-0.0933	-0.0868	-0.114	-0.149
p-val	0.108	0.0170	0.0604	0.0369
50th percentile	-0.0196	-0.0305	-0.0804	-0.0699
p-val	0.694	0.179	0.0645	0.177
90th percentile	0.0724	0.0450	-0.0361	0.0367
p-val	0.363	0.463	0.579	0.633
Panel B. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per acre distribution:				
10th percentile	-0.0949	-0.0747	-0.0771	-0.135
p-val	0.0921	0.141	0.246	0.114
50th percentile	-0.0169	-0.0286	-0.0800	-0.0681
p-val	0.745	0.226	0.0702	0.193
90th percentile	0.0757	0.0265	-0.0834	0.0123
p-val	0.372	0.727	0.235	0.888
Panel C. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per capita distribution:				
10th percentile	-0.0543	-0.0662	-0.0867	-0.124
p-val	0.328	0.0594	0.163	0.111
50th percentile	-0.0183	-0.0265	-0.0787	-0.0645
p-val	0.717	0.252	0.0702	0.209
90th percentile	0.00629	0.00154	-0.0730	-0.0226
p-val	0.918	0.969	0.143	0.721

Notes: This table studies the impact of drought exposure on county-level measures of retail and manufacturing activity. We re-estimate all regressions using the log loans per acre as the measure of ex-ante credit access. Panel B reports the marginal effects from these regressions. Panel C reports the marginal effects when using loans per capita as the measure of ex-ante credit access. All regressions include the log population in 1950 and county area both linearly and interacted with the drought indicator variable; all regressions also include state fixed effects. All regressions include the lag (1950) of the dependent variable. Standard errors, in parentheses, are clustered at the state-level. ***,**,* denote statistical significance at the 10, 5 and 1 percent respectively.

Internet Appendix

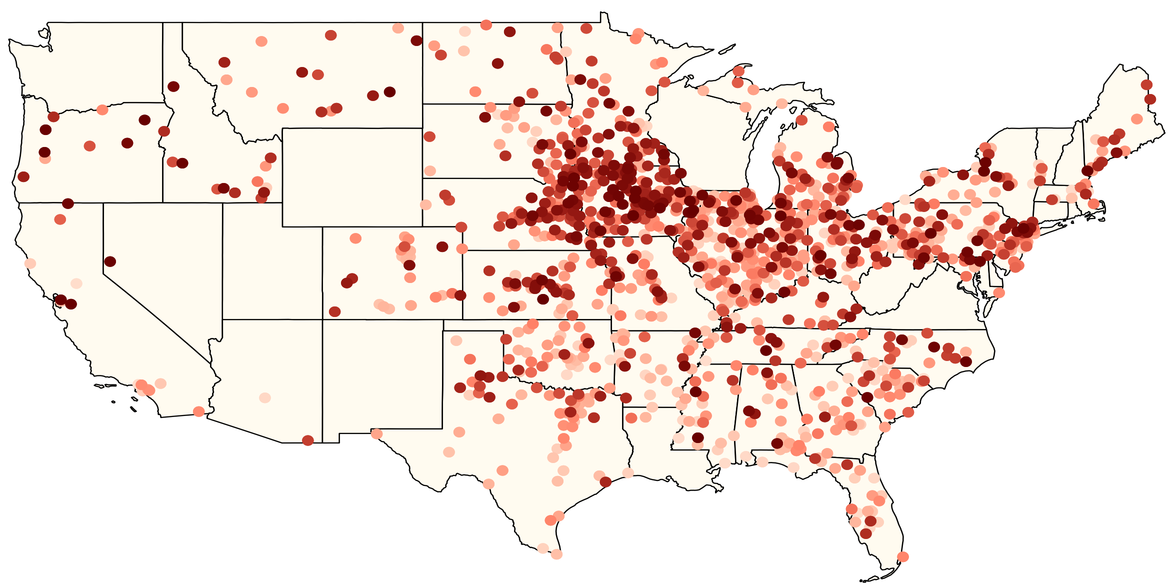
Appendix A1. Supplementary Figures and Tables

Figure A1.1 Drought in the continental United States, 1900-2014



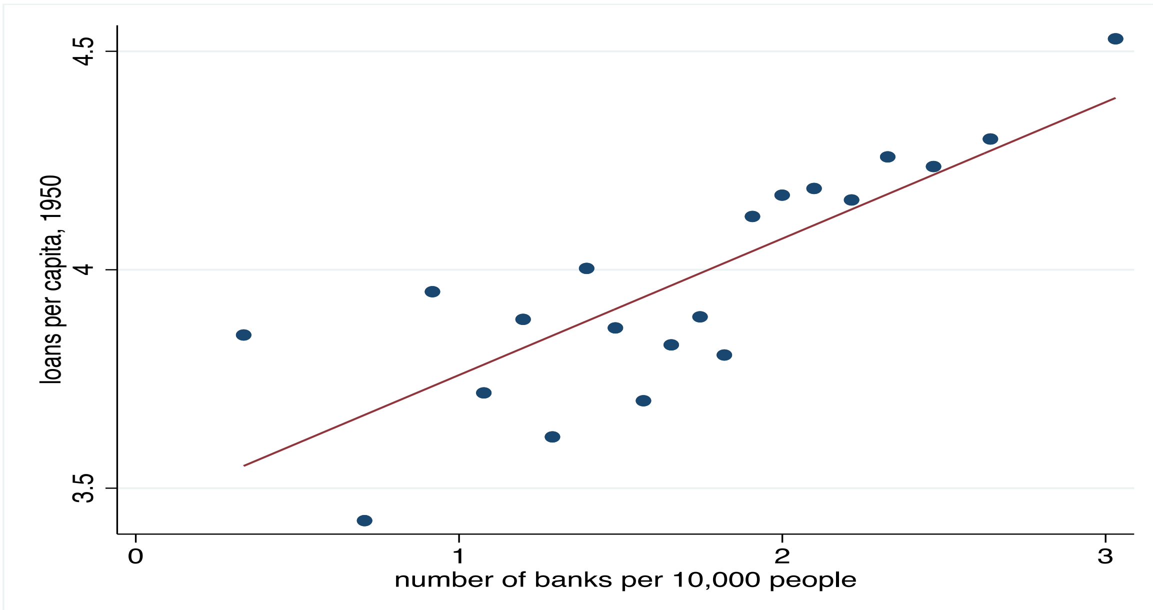
This figure shows the percent area of the continental US experiencing moderate to extreme drought (Palmer Drought Severity Index<-2.00) conditions, Jan 1900-Dec 2014. The black line is the 10 year moving average—see (Heim 2017).

Figure A1.2 Towns in the Sample



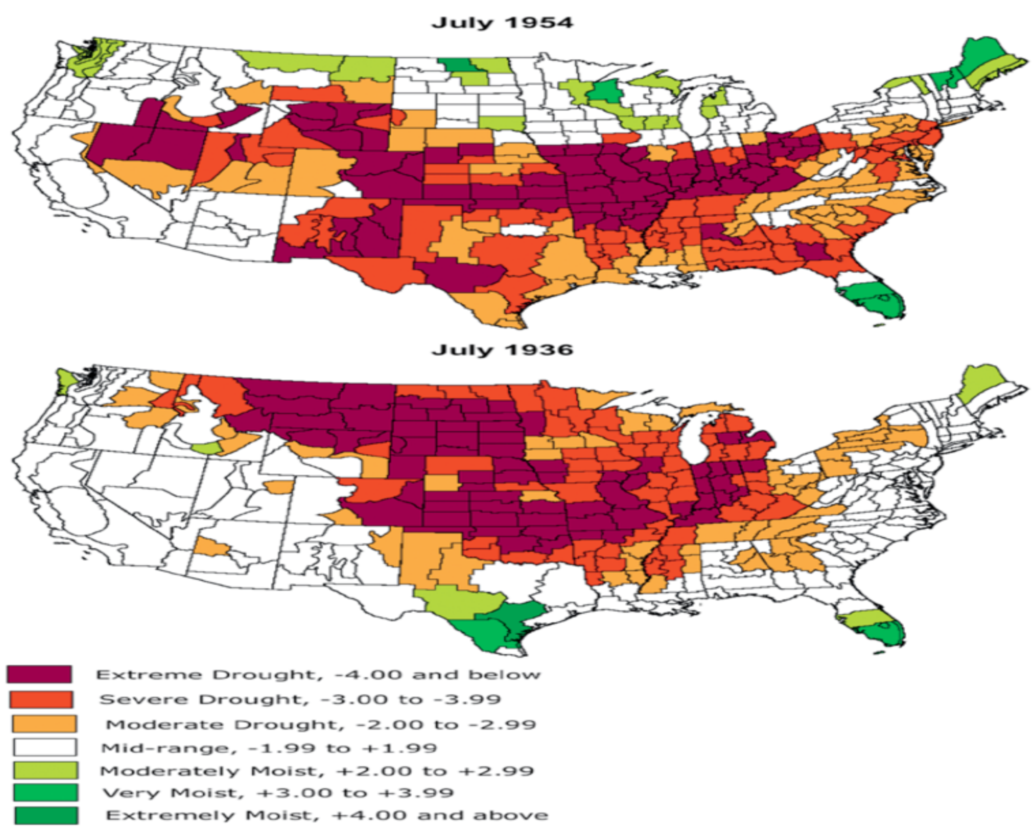
Notes: This figure shows the spatial distribution of the towns in the sample with bank-level data.

Figure A1.3 Log of loans per capita, 1950 vs number of banks per 10,000 people in county



This figure plots a binned scatter plot of loans per capita, 1950 (log) in a county and the number of banks per 10,000 people in the county, also observed in 1950. The two series are first purged of state-fixed effects.

Figure A1.4 The "Dustbowl" and the 1950s drought

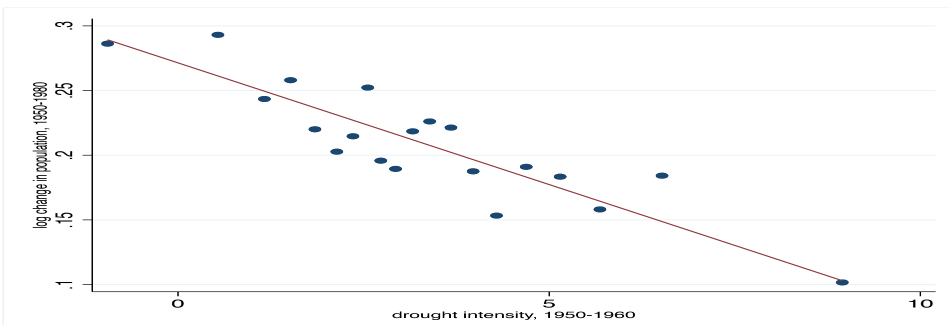


Notes: This figure plots drought intensity using the Palmer Drought Severity Index—see (Heim 2017).

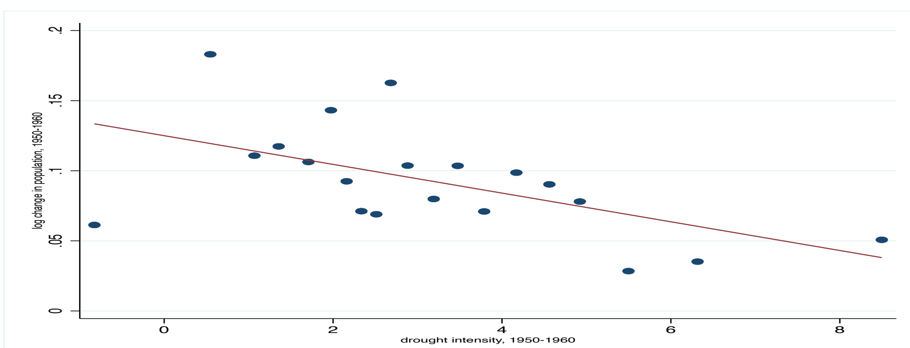
Figure A1.5 Population growth and the 1950s drought

A. Change in county-level population, 1950-1960 and the 1950s drought

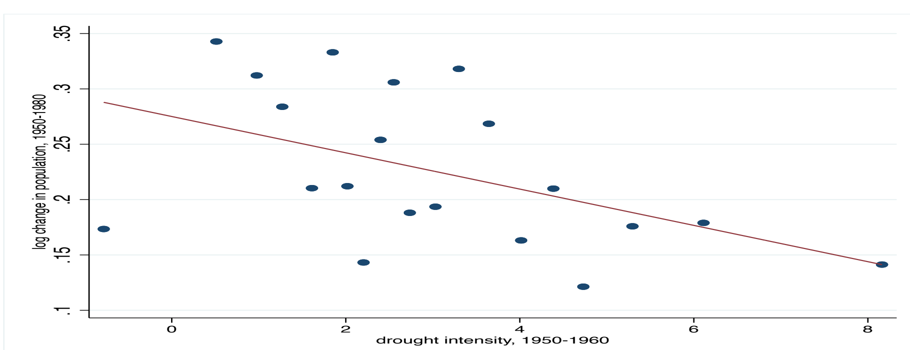
B. Change in county-level population, 1950-1980 and the 1950s drought



C. Change in town-level population, 1950-1960 and the 1950s drought

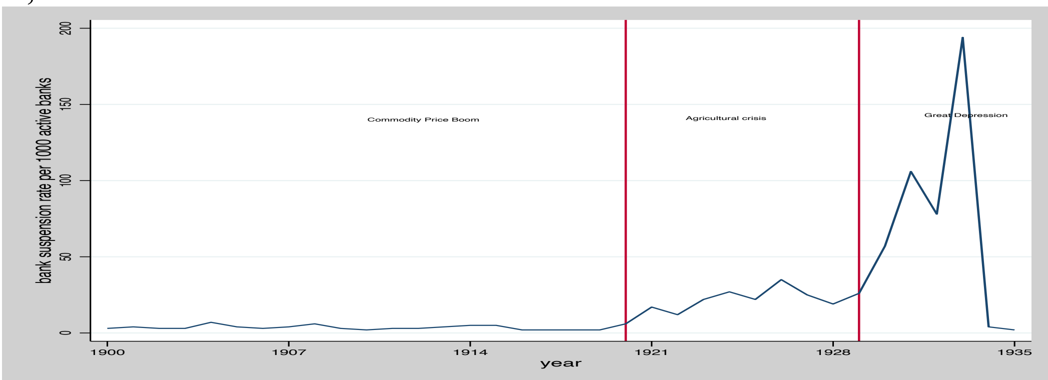


D. Change in town-level population, 1950-1980 and the 1950s drought



Notes: These figures are binscatter plots that illustrate the relationship between population growth at different time and spatial frequencies and drought intensity in 1950-1960 using the SPI.

FigureA1.6 The number of suspended banks per one thousand active banks in the United States, 1900-1935



Source: Federal Reserve Board,1936.

Table A1.1 The share of a county's land area in extreme drought using the Standard Precipitation Index (SPI) during the Dustbowl and the 1950s drought, by census geographic region.

	Mean	SD	Min	Max
		New England		
1950s Drought	2.02	1.45	0	6.17
Dustbowl	2.37	1.31	0.01	5.55
		Mid-Atlantic		
1950s Drought	0.84	0.96	0	5.77
Dustbowl	4.44	2.91	0.03	13.57
		East North Central		
1950s Drought	2.8	2.08	0	8.62
Dustbowl	7.54	3.15	0.52	16.04
		West North Central		
1950s Drought	4.5	3.26	0	15.09
Dustbowl	5.67	3.14	0.05	16.52
		South Atlantic		
1950s Drought	2.33	1.88	0	7.68
Dustbowl	4.23	2.6	0	10.44
Table 1, cont'd				
		East South Central		
1950s Drought	2.54	1.82	0	8.22
Dustbowl	5.64	3.87	0	16.31
		West South Central		
1950s Drought	5.03	3.64	0	20.37
Dustbowl	1.37	1.53	0	9.42
		Mountain		
1950s Drought	4.01	3.13	0	18.3
Dustbowl	3.66	2.83	0	11.62
		Pacific		
1950s Drought	1.56	1.1	0.04	7.31
Dustbowl	4	3.29	0.01	13.03

The county-level data are from the National Oceanic and Atmospheric Administration

Table A1.2 Sources of farm credit, 1950

		Non-real estate		Real estate		All	
		$ (million)	%	$ (million)	%	$ (million)	%
Banks		2,048	39.9%	937	16.8%	2,985	27.9%
Merchants and Dealers		2,300	44.8%	0	0.0%	2,300	21.5%
Life Insurance Companies		0	0.0%	1,172	21.0%	1,172	10.9%
Individuals		0	0.0%	2,312	41.4%	2,312	21.6%
Non-market		784	15.3%	1,158	20.8%	1,942	18.1%
Total		5,132		5,579		10,711	

Source: Agricultural Credit and Related Data, 1968, American Bankers Association. Non-market sources include the Farmers Home Administration; Production Credit Associations and Federal Land Banks.

Table A1.3 Summary statistics: Adaptation and Investment

	Number of trucks and automobiles per farm, 1969		Number of tractors per farm, 1969		Loans per farm, 1950 ($)
	Farms with sales < $2,500	Farms with sales >$2,500	Farms with sales < $2,500	Farms with sales >$2,500	
N	985	986	985	986	994
Mean	1.57	2.43	1.01	2.19	694.41
SD	0.26	0.5	0.28	0.55	182.9
Min	0.62	0.86	0.26	0.29	43.92
Max	3.44	5.14	2.29	5.29	2143.91

	Change in irrigated land (%)		Change in farm land acreage (%)		Share of land area in agriculture, 1969	Value of land and buildings: Average per farm ($), 1969
	1949-1959	1959-1969	1949-1959	1959-1969		
N	977	977	989	989	989	986
Mean	3.3	0.65	-0.11	0.49	0.64	82352.79
SD	2.62	1.89	0.21	0.64	0.3	60713.95
Min	-5.56	-6.15	-1.31	-0.65	0	11759
Max	10.12	6.27	2.34	4.4	1.25	663904

This table reports summary statistics for US counties. The sample is restricted to counties that are covered in the banking data. Source: US Census of Agriculture.

Table A1.4 Age Distribution, 1960

	(1) age<20 years	(2) 20s	(3) 70s	(4) median age, 1960	(5) median age, 1980
4th quartile drought intensity, 1950-1960	-0.0835*** (0.0216)	-0.0201* (0.0107)	0.0408*** (0.0129)	0.298*** (0.0680)	0.234** (0.0916)
log loans per capita, 1950	0.000322 (0.000580)	0.00000113 (0.000341)	-0.0000216 (0.000275)	-0.00176 (0.00171)	-0.00332 (0.00215)
4th quartile drought intensity*loans per capita	0.00223** (0.00106)	0.000758 (0.000732)	-0.000938 (0.000645)	-0.00894** (0.00415)	-0.00841** (0.00399)
N	988	988	988	988	988
adj. R^2	0.794	0.783	0.824	0.806	0.433
mean	0.395	0.110	0.0701	3.381	3.427
sdev	0.0383	0.0233	0.0212	0.142	0.105
The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per capita distribution:					
10th percentile	-0.00537	-0.00397	0.00263	0.0249	0.0218
p-val	0.0324	0.0102	0.0879	0.00820	0.0360
50th percentile	-0.00141	-0.00262	0.000964	0.00897	0.00688
p-val	0.568	0.000429	0.407	0.253	0.354
90th percentile	0.00134	-0.00168	-0.000196	-0.00209	-0.00352
p-val	0.678	0.144	0.896	0.843	0.696

Notes: This table examines the impact of drought exposure on the age distribution in counties. The dependent variables in columns 1-4 are observed in 1960. All regressions include state fixed effects, and linearly include the log population in 1950, as well as interacted with the top quartile drought indicator variable. All regressions also include an analog of the dependent variable observed in 1950. For example, column 2 includes the fraction of the population aged 20-29 years in 1950. The dependent variable in column 1 is the fraction of the population less than 20 years old. The dependent variables in column 2 is the fraction of the population 20-29 years old in the population; column 3: the fraction of the population older than 69 years old; Columns 4 and 5 use the log of the median age in 1960 and 1980 respectively. Standard errors in parentheses and are clustered at the state level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A1.5 Marginal impact of drought exposure, based on Table 7

	population growth, 1950-1960	population growth, 1950-1980	loan growth, 1950-1960
	In-town, 10th percentile credit		
In-state, 10th percentile credit	-0.0347	-0.0134	0.0407
p-value	0.459	0.884	0.709
In-state, 50th percentile credit	-0.0653	-0.131	-0.303
p-value	0.0899	0.107	0.00562
In-state, 90th percentile credit	-0.107	-0.289	-0.775
p-value	0.0258	0.0427	0.00462
	In-town, 50th percentile credit		
In-state, 10th percentile credit	0.0181	-0.0289	0.0295
p-value	0.570	0.644	0.661
In-state, 50th percentile credit	-0.0159	-0.0430	-0.0930
p-value	0.594	0.435	0.128
In-state, 90th percentile credit	-0.0626	-0.0620	-0.261
p-value	0.0940	0.333	0.00397
	In-town, 90th percentile credit		
In-state, 10th percentile credit	0.0715	-0.0445	0.0183
p-value	0.259	0.705	0.919
In-state, 50th percentile credit	0.0341	0.0456	0.119
p-value	0.460	0.666	0.377
In-state, 90th percentile credit	-0.0174	0.167	0.257
p-value	0.698	0.374	0.146

This table reports the marginal impact of drought exposure using the estimates in Table 7. For example, from column 1 drought exposure implies a 3.47 (p-value=0.459) percentage point decline in population growth (1950-1960) for a town at the 10th percentile of per capita credit located next to in-state towns at the 10th percentile of per capita credit. But drought exposure implies a 6.53 (p-value=0.08) and a 10.7 (p-value=0.02) decline in population growth (1950-1960) respectively for a town at the 10th percentile of per capita credit located next to in-state towns at the 50th and 90th percentiles of per capita credit.

Table A1.6 Investment, Technological Adaptation and Groundwater Irrigation: The Marginal Impact of Drought Exposure

	Mean trucks and cars (1)		Mean tractors (2)	
Loans per farm	Ground water at 10th percentile	Ground water at 90th percentile	Ground water at 10th percentile	Ground water at 90th percentile
10th percentile	-0.0347	-0.0125	-0.0644	0.00153
p-val	0.0364	0.711	0.0105	0.981
50th percentile	-0.0175	0.0346	-0.0437	0.0679
p-val	0.366	0.228	0.111	0.114
90th percentile	0.00365	0.0923	-0.0184	0.149
p-val	0.918	0.0823	0.723	0.000

This table presents the marginal effects of drought exposure for regressions that interact top quartile drought exposure with log loans per farm in 1950 and log farm acreage irrigated by groundwater in 1959, along with all their subcomponents. The regressions also include state fixed effects and log population and area in 1950 both linearly and interacted with the drought indicator variable. The dependent variable in column 1 is the log mean number of trucks and cars on farms with annual sales less than $2,500. The dependent variable in column 2 is the log mean number of tractors on farms with annual sales less than $2,500. The column labelled "Ground water at 10th percentile" reports the marginal impact of drought exposure over the distribution of loans per farm when ground water is at the 10th percentile. The column labelled "Ground water at 90th percentile" reports the marginal impact of drought exposure over the distribution of loans per farm when ground water is at the 90th percentile. In all cases, these marginal effects hold constant the other covariates at the mean levels.

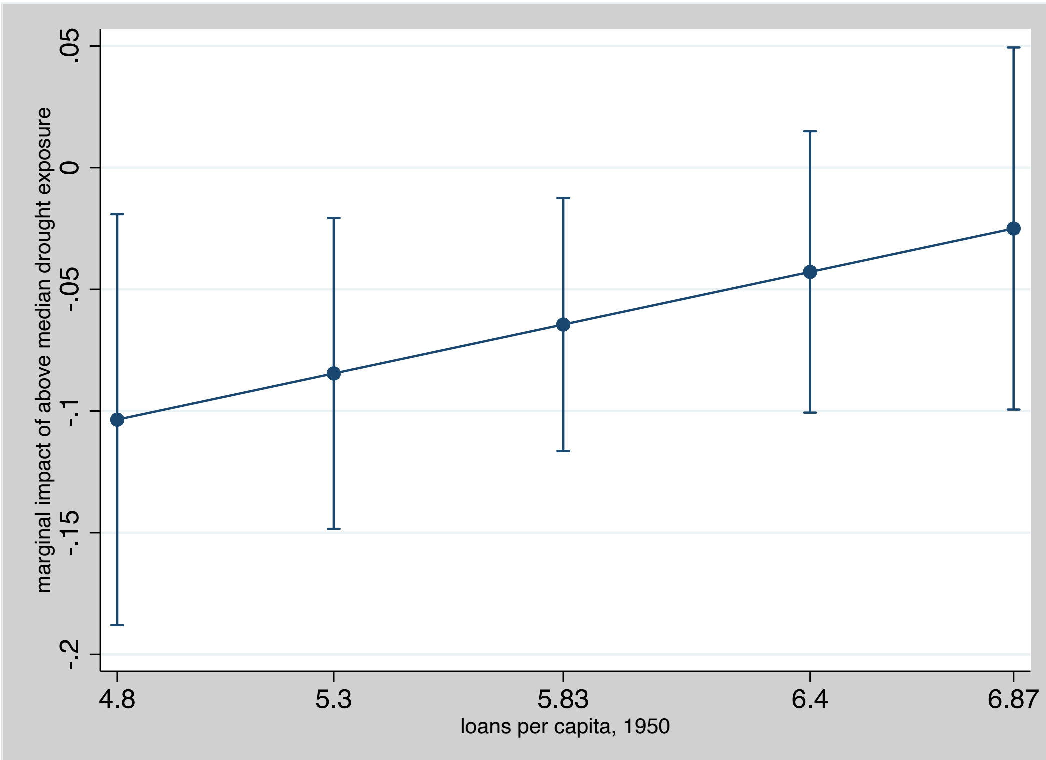
Table A1.7 Mean farm sizes

	(1) mean farm size, 1959	(2) mean farm size, 1982
4th quartile drought intensity, 1950-1960	0.254	0.570
	(0.213)	(0.492)
log loans per farm 1950	0.00732*	-0.00750
	(0.00408)	(0.00836)
4th quartile drought intensity*loans per farm	0.0269	0.0262
	(0.0241)	(0.0159)
N	983	978
adj. R^2	0.971	0.882
mean	5.323	5.624
stdev	0.827	0.800
Panel A. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per farm distribution:		
10th percentile	-0.0245	-0.0115
p-val	0.401	0.799
50th percentile	0.0225	0.0346
p-val	0.267	0.285
90th percentile	0.0842	0.0906
p-val	0.251	0.0454
Panel B. The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per acre distribution:		
10th percentile	-0.0400	-0.00457
p-val	0.390	0.918
50th percentile	0.0241	0.0360
p-val	0.270	0.271
90th percentile	0.102	0.0838
p-val	0.297	0.129

Notes: This table studies the impact of drought exposure on mean farm sizes. We re-estimate all regressions using the log loans per acre as the measure of ex-ante credit access. Panel B reports the marginal effects from these regressions. All regressions also include state fixed effects and log population and area in 1950 both linearly and interacted with the drought indicator variable; all regressions include the lag (1950) of the dependent variable. Standard errors, in parentheses, are clustered at the state-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

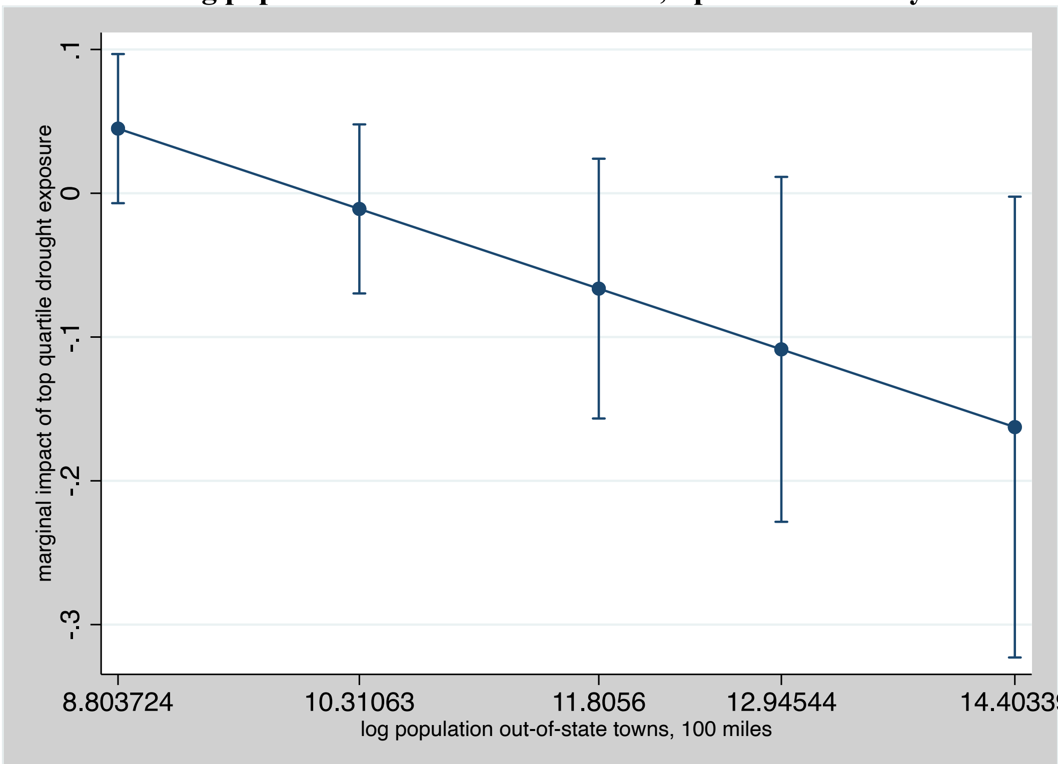
Appendix A2 Additional robustness checks

Figure A2.1 The marginal impact of above median drought exposure on population growth, 1950-1960, as a function of loans per capita, 1950, log



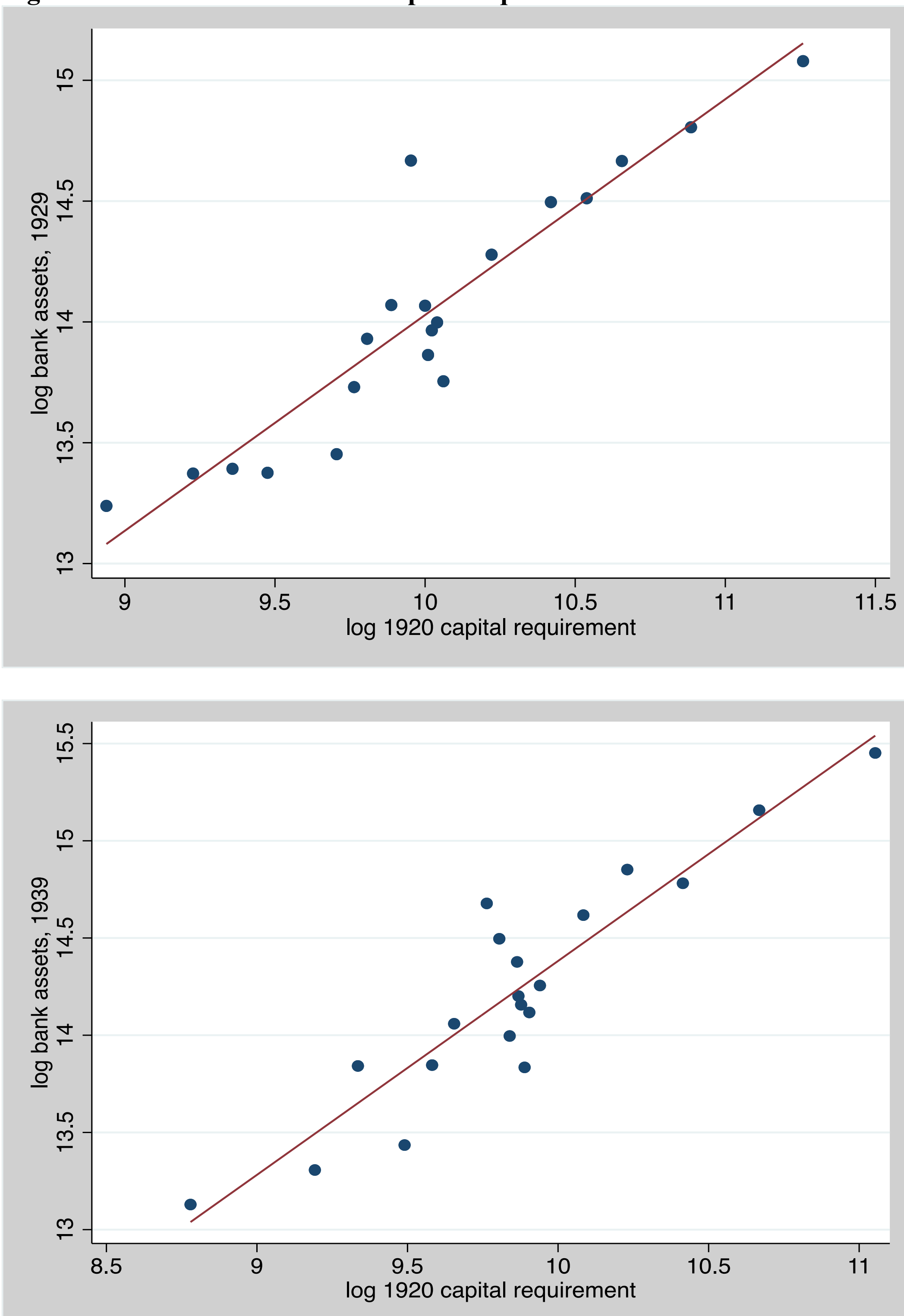
Notes: This figure is a modified version of column 4 of The modified regression replaces "top quartile drought exposure" with "above median drought exposure". The figure plots the marginal impact of above median drought exposure on town-level population growth, 1950-1960, over the 1950 loans per capita distribution.

Figure A2.2 The marginal impact of drought exposure on population growth, 1950-1960, as a function of the log population in out-of-state towns, up 100 miles away



Notes: This figure is based on column 4 of Table 7 (but uses a 100 mile distance window). It plots the marginal impact of drought exposure—based on the top quartile drought indicator variable—over the support of the log of the out-of-state population distribution in towns up to 100 miles away. The points on the *x*-axis are the 10th, 25th, 50th, 75th and 90th percentiles of the log population in out-of-state towns up to 100 miles away.

Figure A2.3 Bank size and 1920 capital requirement



Notes: These binscatter plots are based on bank-level regressions with the log bank assets as the dependent variable. Controls include state-fixed effects, the town's population in 1920, and an indicator variable that equals if the bank is a national bank. The elasticity in the top panel is 0.89 (p-value<0.00) and 1.10 (p-value<0.00) in the bottom panel.

Appendix A3. Town-level evidence

Table A3.1 The impact of drought exposure on population growth—town-level evidence

	(1) all towns	(2) in-sample	(3) non-linear	(4) baseline	(5) 1950-1980
drought intensity, 1950-1960, SPI continuous measure	-0.0107**	-0.0115**			
	(0.00448)	(0.00537)			
2nd quartile drought intensity, 1950-1960			-0.0134		
			(0.0300)		
3rd quartile drought intensity, 1950-1960			-0.0587		
			(0.0356)		
4th quartile drought intensity, 1950-1960			-0.0896**	-0.573***	-0.886**
			(0.0410)	(0.172)	(0.373)
log loans per capita, 1950				0.0442**	0.0816**
				(0.0191)	(0.0306)
4th quartile drought intensity*loans per capita				0.0371	0.0380
				(0.0245)	(0.0643)
N	1790	1302	1302	1302	1187
adj. R^2	0.084	0.074	0.075	0.090	0.140
The marginal effect of top quartile drought exposure, evaluated at the 10th, 50th and 90th percentiles of the log loans per capita distribution:					
10th percentile				-0.086	-0.168
p-val				0.018	0.014
50th percentile				-0.049	-0.130
p-val				0.172	0.022
90th percentile				-0.011	-0.093
p-val				0.836	0.357

Notes: This table examines the impact of drought exposure on the log change in population among incorporated towns. The dependent variable in columns 1-4 is the log change in population between 1950-1960; the dependent variable in column 5 is the log change in population between 1950-1980. All regressions include state fixed effects, and linearly include the log population in 1950, as well as interacted with the top quartile drought indicator variable. Standard errors in parentheses and are clustered at the state level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.2 Spatially corrected standard errors

	(1) 100km	(2) 200km	(3) 300km	(4) 500km	(5) 1000km
log loans per capita, 1950	0.0391*** (0.0133)	0.0391*** (0.0124)	0.0391*** (0.0127)	0.0391** (0.0161)	0.0391*** (0.0115)
4th quartile drought intensity*loans per capita	0.0456* (0.0274)	0.0456* (0.0275)	0.0456** (0.0202)	0.0456*** (0.0176)	0.0456*** (0.0116)
4th quartile drought intensity, 1950-1960	-0.617*** (0.220)	-0.617*** (0.198)	-0.617*** (0.146)	-0.617*** (0.176)	-0.617*** (0.0159)
N	1267	1267	1267	1267	1267
adj. R^2	0.019	0.019	0.019	0.019	0.019

Notes: This table replicates the baseline town-level regression in column 4 of Table A2.1 but reports standard errors corrected for spatial dependence ((Conley 1999) at distances from 100km (column 1) through 1000km (column 5).

Appendix A4. Town-level capital requirements identification strategy

Table A4.1 The Number of Banks in the US, 1910-1920

Year	State Banks	National Banks
1910	14,348	7138
1911	15322	7270
1912	16,037	7366
1913	16,841	7467
1914	17,498	7518
1915	17,748	7597
1916	18,253	7571
1917	18,710	7599
1918	19,404	7699
1919	19,646	7779
1920	20,635	8024

source: The Dual Banking System in the United States, 1933

Table A4.2 provides evidence supporting the identification strategy. Using state capital regulations and population data from the US Census, we determine the log of a town's minimum capital requirement in 1910. If entry capital requirements did indeed shape entry and survival, then towns subject to higher capital requirements in 1910, and thus shielded from the proliferation of smaller less stable banks during the 1910s boom, should have more banks left after the commodity bust. The dependent variable in column 1 is the per capita number banks in the town in 1929. Because the capital requirement was based in part on the town's population in 1910, all regressions include the log of the town's population in 1910 to absorb any mechanical direct effect of the 1910 population on banking outcomes; state fixed effects absorb the political and economic factors at the state-level that might drive the use of these capital regulations.

The results show that by 1929—about 8 years after the initial collapse in commodity prices—towns with higher capital requirements in 1910 had more banks per capita in 1929. However, the relationship between the 1910 capital requirement and the spatial variation in local banking sharpens after the banking panics of the Depression. In column 1, a one standard deviation increase in the 1910 capital requirement is associated with about a 0.48 standard deviation increase in the number of banks per capita in 1929 (p-value=0.09). Column 2 uses the percent

Table A4.2 The impact of the 1910 state capital requirement on banking across towns, 1929-1950

VARIABLES	(1) number of banks per capita, 1929	(2) Change in number of banks, 1929-1939	(3) Number of banks per capita, 1939	(4) Number of banks per capita, 1950
1910 capital requirement, log	0.000264*	0.118*	0.000340***	0.000355**
	(0.000154)	(0.0602)	(0.000120)	(0.000136)
1910 population, log	-0.000538***	-0.0670***	-0.000423***	-0.000463***
	(8.00e-05)	(0.0199)	(5.70e-05)	(6.99e-05)
Observations	1,220	1,217	1,211	1,220
R-squared	0.565	0.101	0.472	0.504

Notes: This table studies the relationship between a town's 1910 capital requirement and subsequent banking outcomes. All regressions include state-fixed effects and standard errors, in parentheses, are clustered at the state-level, and ***,**,* denote statistical significance at the 10, 5 and 1 percent respectively.

change in the number of banks between 1929 and 1939. A one standard deviation increase in the 1910 capital requirement is associated with a 26 percentage point change in the number of banks (p-value=0.06). Note that the mean change during this period was -53.4 percent, as towns in the sample lost on average about half their banks.

In keeping with this evidence, column 3 shows that the same increase in the 1910 capital requirement suggests a 0.78 standard deviation increase in the per capita number of banks in 1939 (p-value<0.01). Moreover, the elasticity between the log of bank assets and the log of the 1910 capital requirement using bank-level regressions for banks present in 1929 is 0.89 (p-value<0.00) and 1.10 (p-value<0.00) for surviving banks in 1939—the corresponding binscatter plots are in IA Figure A2.3. That is, not only did higher entry capital requirements reduce bank failures, but these requirements also left behind larger banks post-Depression.

Of course, if new banks entered those towns that experienced bank failures during the Depression, then the 1910 capital requirement might explain little of the variation in potential loan supply in 1950. However, post-Depression banking regulation generally limited spatial competition in banking until the deregulation wave begun in the 1970s, making it unlikely that new entrants quickly filled the void left by the Depression era failures. Consistent with this fact, column 4 shows that the 1920 capital requirement shaped local market structure through 1950.

The dependent variable in column 4 is the per capita number of banks in 1950. A one standard deviation increase in the 1920 capital requirement suggests a 0.68 (p-value=0.01) standard deviation increase in the per capita number of banks in 1950. That is, towns with higher capital requirements before the Depression had more banks left behind after the Depression-era wave of bank failures at least up through 1950.

State-level banking regulations determine the relationship between a town's 1910 population and the 1910 capital entry requirement for the town. However, because of location fundamentals and agglomeration economies, relatively bigger towns in 1910 within the state, with their concomitant higher capital requirements, would likely retain their relative position in the town-size distribution in 1950. And the statistical relationship between the 1910 capital requirement and 1950 banking outcomes might reflect the town's 1950 population and the size of the local market itself in 1950 rather than capital entry requirements and selective survival. Moreover, because bigger towns tend to be wealthier and have better transport networks, the 1950 population can independently determine the drought's impact, violating the exclusion restriction assumption.

IA Table A4.3 addresses this concern. It checks whether controlling for population in 1950 affects the relationship between the 1910 capital requirement and the log of 1950 per capita bank credit. The dependent variable is the log of per capita credit, and column 1 includes the log of the 1950 population as a control variable. The point estimate on the 1910 capital requirement remains positive and significant. As a robustness exercise, columns 2-5 of IA Table A4.3 controls for the 1950 log population using increasingly higher order polynomials up to the 5th order (column 5). Throughout, the point estimate on the 1920 capital requirement remains relatively stable. Next, column 6 models the 1950 population using a spline function based on the most common regulatory population breakpoints. These are indicator variables for whether a town has less than 3,000 people; between 3,000 and 6,000 people; between 6,000 and 25,000 people and between 25,000 and 50,000 people; more than 50,000 people is the omitted category. The results remain unchanged.

Table A4.3 The impact of the 1910 state capital requirement on log credit per capita, 1950

VARIABLES	(1) Linear	(2) 2^{nd} order	(3) 3^{rd} order	(4) 4^{th} order	(5) 5^{th} order	(6) Break-points
1910 capital requirement, log	0.299**	0.211*	0.206*	0.239**	0.218*	0.293**
	(0.116)	(0.111)	(0.111)	(0.117)	(0.114)	(0.118)
Observations	1,184	1,184	1,184	1,184	1,184	1,184
R-squared	0.265	0.297	0.297	0.299	0.298	0.265

Notes: This table studies the impact of the 1910 capital requirement on 1950 log credit per capita in the town. All regressions include state fixed effects and the log of population in 1920. In addition, column 1 includes linearly the log population in 1950; column 2 includes this variable up to a polynomial of order 2; in column 3 the order of the polynomial is 3; in column 4 the order of the log population in 1950 polynomial is 4; in column 5 the polynomial is of order 5; column 6 models log population in 1950 using a spline function based on the capital regulation: These are indicator variables for whether a town has less than 3,000 people; between 3,000 and 6,000 people; between 6,000 and 25,000 people and between 25,000 and 50,000 people; more than 50,000 people is the omitted category. Column 7 is the formal first stage regression an the regression includes the log population in 1950 interacted with the top quartile drought indicator variable. Standard errors, in parentheses, are clustered at the state-level, and ***,**,* denote statistical significance at the 10, 5 and 1 percent respectively.