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Are Banks Responsive to Exogenous Shocks to Credit Demand in Rural Economies? District – level Evidence from India

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September 2015

Abstract

In the existing literature on rural financial markets in emerging economies, there has been much discussion on local bilateral contracts and mutual insurance arrangements, which are inadequate to deal with the typically correlated risks that individuals and households face in the rural sector. There have been discussions also on the costly and inefficient strategies that the households adopt to smooth their income or consumption. The discussions rest on the implicit premise that the financial intermediation system in the rural economy is inefficient in insuring the individual agents against idiosyncratic shocks to their income and consumption. However, the premise itself has remained largely unexamined. Using extensive district-level rainfall and bank credit data from India, we investigate whether the commercial banks respond positively to exogenous shocks to credit demand in the rural economy in the wake of droughts. We find that banks increase agricultural credit in drought-affected years compared to years of normal rainfall, but not personal loans or other types of non-agricultural credit. Further, agricultural credit increases in the intensive margin (average loan size per account), but not in the extensive margin (the number of accounts). We also find that private banks increase credit more than public-sector banks. Overall, our findings offer positive evidence on the role of commercial banks in rural financial markets and, in the process, contribute to several existing literatures.

Keywords: bank credit; credit demand; credit supply; natural disasters

***JEL* Classifications:** G21, O2, Q14

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In the existing literature on rural financial markets in emerging economies, there has been much discussion on local bilateral contracts and mutual insurance arrangements, which are inadequate to deal with the typically correlated risks that individuals and households face in the rural sector. There have been discussions also on the costly and inefficient strategies that the households adopt to smooth their income or consumption. The discussions rest on the implicit premise that the financial intermediation system in the rural economy is inefficient in insuring the individual agents against idiosyncratic shocks to their income and consumption. However, the premise itself has remained largely unexamined. Using extensive district-level rainfall and bank credit data from India, we investigate whether the commercial banks respond positively to exogenous shocks to credit demand in the rural economy in the wake of droughts. We find that banks increase agricultural credit in drought-affected years compared to years of normal rainfall, but not personal loans or other types of non-agricultural credit. Further, agricultural credit increases in the intensive margin (average loan size per account), but not in the extensive margin (the number of accounts). We also find that private banks increase credit more than public-sector banks. Overall, our findings offer positive evidence on the role of commercial banks in rural financial markets and, in the process, contribute to several existing literatures.

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I. Introduction and motivation

"*While these studies have advanced our understanding of local bilateral financial contracting and mutual insurance within poor communities, the study of financial intermediation has remained relatively neglected"* (Conning and Udry, "Rural Financial Markets in Developing Countries", Handbook of Agricultural Economics, 2007)

How effectively does the financial intermediation system respond to idiosyncratic shocks to income and consumption faced by households in the rural sector of an emerging economy? In spite of the enormous importance of the topic, a survey of the existing literature on rural financial markets finds hardly any studies directly addressing the topic. By contrast, local bilateral credit and insurance arrangements with landlords, moneylenders, family and friends, or group-based mutual savings and insurance arrangements such as rotating savings and credit associations (ROSCAs) have received much attention (see, for example, Coate and Ravallion, 1993; La Ferrara 2003; Townsend 1995; Genicot and Ray, 2002). However, since the risks that individuals and households face in a rural economy are typically correlated, as they arise from common external shocks such as floods and famines, and the pool of savings are usually limited, local markets often fail to offer adequate diversification opportunities at a reasonable cost. As a result, households and individuals in rural areas are left facing considerable residual risk, with no option but to adopt costly and inefficient strategies to smooth income or consumption. A number of such strategies have been discussed in the existing literature, including scattering plots of cultivable land (McCloskey 1976; Townsend 1993) and opting for a more diversified mix of crops and nonfarm production activities at the price of a lower average return, adjustment of intertemporal labor supply in response to shocks (Kochar 1999), labor bonding (Srinivasan 1989; Genicot 2002), selling investment assets to smooth consumption (Rosenzweig and Wolpin, 1993) and several other options. Not surprisingly, the welfare implications of the strategies are typically negative.

While the discussions in the existing literature have been insightful and advanced our understanding of the strategies and their limitations, they rest on the implicit premise that risk diversification opportunities offered by the existing system of financial intermediation in a rural economy are either very limited or altogether missing. However, the premise itself has remained largely unexamined. The quotation at the beginning of this section from a review article by

Conning and Udry on rural financial markets in developing economies published in 2007 remains apt even today. The present paper is an attempt to redress this imbalance in the existing literature on rural financial markets. The paper examines the premise with multiple tests conducted with extensive data of bank credit and rainfall shocks at the district level in India, and finds that the commercial banking system in the rural economy of India responds positively to exogenous shocks to credit demand following adverse rainfall shocks. This is the central contribution of the present paper. In the process, the paper makes contributions to several other literatures as well. The present paper is also the first systematic study of the relationship between the two primary determinants of farm output in India and other emerging economies: rainfall and supply of credit.

Our approach links the responsiveness of the commercial banks to exogenous credit demand shocks following adverse rainfall to the bankers' incentive structure. To motivate our approach, a numerical analysis exercise using actual rainfall data and multiple realistic scenarios is presented in an appendix (see Appendix 1 at the end of this paper). The exercise incorporates a standard feature of rural credit cycles and a few typical features of bankers' incentives that have been documented by other researchers (Banerjee, Cole and Duflo, 2005; Banerjee and Duflo, 2008). The farmers seek bank credit for their operating expenses (seeds, fertilizers etc.) during the crop planting season and, in a year of normal rainfall, pay off their debt from the proceeds of the harvest. In a year of poor rainfall, their ability to pay off their current debt is impaired, and some of them default. But they still need a fresh loan for the next planting season. The bankers face a penalty if they recognize a bad loan, and prefer to bailout the defaulting farmers and give them fresh loans provided the expected value of the future default (and consequent penalty) is less than the certain value of the current default. In many cases, bailouts substitute the probability of a bigger future default for the certainty of a smaller current default. But this is not so in the case of drought-driven defaults, because a year of drought is typically followed by a year of normal rainfall[1]. This intuition leads to several testable predictions. We summarize them here, but discuss them more fully in section III of this paper. First, the volume of outstanding agricultural credit extended by banks increases following a year of poor rainfall, driven by those

[1] In our sample, using one measure of drought, a district experiences a drought in two consecutive years in 15.3% cases, compared to average occurrence of drought in 11.3% district-years. By a second measure of drought, the corresponding numbers are 15.3% and 17.5%.

farmers who are unable to pay off their current loans but still get fresh loans. Second, the credit increase occurs in the intensive margin (the average size of the existing loans) rather than in the extensive margin (the number of loan accounts). The bankers typically have more information about the type of their current borrowers than they have about new borrowers. Following a difficult year their information set is more refined, and they are better able to target better farmers within their current pool of borrowers for more credit. Third, while bank managers with both public sector and private sector banks like to bail out a farmer in default and not recognize a non-performing loan, public sector bank managers typically face stiffer penalties for bad loans (Banerjee, Cole and Duflo, 2005; Banerjee and Duflo, 2008). As a result, public sector banks are observed to respond more positively than private banks to combined credit demand from farmers of all types. We test the empirical implications with district-level data of rainfall and credit supply in India during 1994 – 2010 and find strong supporting evidence. Multiple robustness tests confirm our findings.

The present paper contributes to several other existing literatures as well. In standard neo-classical model of financial intermediation the primary role of financial institutions is to channel capital from depositors and other savers to uses with the highest marginal returns. Substantial empirical evidence from emerging capital markets suggests that this role is performed poorly. Banerjee and Duflo (2005) cite evidence that in many less developed countries borrowing interest rates are often of the order of 60% or more, even though deposit rates are less than half as much, and defaults are rare. The evidence suggests that the marginal product of capital in the firms paying these rates may far exceed the opportunity cost of capital. In a separate paper, using a sample of loan data from a public sector bank in India, Banerjee and Duflo (2014) use a government-mandated directed lending program as a natural experiment to establish that many of the firms in their sample were severely credit constrained, and that the marginal rate of return to capital was very high for them. To explain their findings, the authors cite aversion to managerial risk-taking in public sector banks. If a loan performs poorly, the managers face a penalty but, on the other hand, a good loan decision does not bring them proportionate rewards. It should be noted that the above studies focus on credit for small businesses, not rural credit. Conceivably, agricultural loans to farmers in drought-affected areas are likely to have high marginal returns, or at least higher marginal returns than during normal times. A drought typically depletes their savings, causing serious capital scarcity[2]. Our finding that banks in rural India increase agricultural credit following a drought compared to non-drought years suggests that allocation of bank credit is not always sub-optimal.

Though this is not the main focus of this paper, our setting also provides a test of the joint effect of electoral processes and drought on credit allocation. Public sector banks are known to be vulnerable to political capture, and loans can be targeted in ways that many other government expenditures, such as public works projects, cannot. Starting with Wright (1974), this literature connects government-mandated provision of bank credit with electoral goals. In two parallel papers, Cole (2009a) and Cole, Healy and Werker (2012) document political capture of public institutions in India, including commercial banking and public distribution systems, resulting in significant differences in provision of agricultural credit and government relief spending at the district level between election and non-election years. In the present paper we use a larger panel dataset, including more districts as well as more years, and investigate the *joint* effects of elections and droughts on agricultural credit and test whether firm credit increases in election years following a drought after controlling for the effect of the drought itself. For all bank groups together as well as each bank group, our difference-in-difference-in-difference tests do not find evidence of increase in agricultural credit beyond what is typically observed following a drought-affected year. However, all bank groups appear to increase credit in years preceding elections in state assemblies. To this extent, our results are consistent with Cole (2009a).

A final contribution of this paper is that it presents the first systematic study of the relationship between the two primary determinants of farm output in India: rainfall and supply of credit. Empirical evidence regarding the relationship is important for our purpose. Agriculture remains a major sector of the Indian economy. It accounts for about 19 per cent of the GDP. The importance of the sector to India is due also partly to its role in job creation and poverty alleviation in the countryside. About two-thirds of the Indian population depend on the sector for their livelihood. In the existing academic literature as well as professional reports, there is sufficient evidence of the importance of rainfall and, to a lesser extent, of rural credit to agricultural output in India. However, there does not appear to be an existing empirical study that links rainfall and rural credit. We discuss this point more fully in the next section.

[2] Rosenzweig and Wolpin (1993) have documented that farmers in India sell their main investment assets, such as bullocks, to smooth consumption during times of poor weather.

Our setting is particularly suitable for the goals of the paper. Our panel data of droughts and agricultural credit at the district level spans 640 districts spread over 28 states and 7 Union Territories over a long period (1993 – 2010). The data offers two types of variation at the district level which are important for our purpose: considerable cross-sectional variation between credit observations and cross-sectional and time-series variation in rainfall deficiency at the district level (see section III of this paper for data description). We exploit the variation in the data to conduct clean difference-in-difference tests to identify the causal impact of unanticipated changes in the demand for farm credit due to exogenous changes in rainfall on the supply of farm credit. The panel-setting enables us to include district fixed-effects in our regression models, ruling out spurious correlations due to time-invariant cross-sectional variations. Similarly, year-fixed effects control for yearly variation in macroeconomic and other factors that may affect supply of agricultural credit. We also use state-year fixed effects to control for time-trends in credit supply so that the regression coefficients reflect the relationships between droughts and agricultural credit net of trends unrelated to droughts.

Our paper proceeds in the following manner. Section II outlines the institutional context for our study. Section III presents our hypotheses regarding agricultural credit supply in response to droughts. Section IV describes the data used to test the hypotheses. Section V presents the results of our basic tests concerning credit supply following a drought. Whether government banks and private banks differ in their response to droughts is the topic of section VI. Section VII presents results on the interaction of the election cycle with the rural credit cycle. Section VIII presents the results of our investigations into the effectiveness of the central banks interventions in rural credit markets in the wake of droughts. Section IX presets our conclusions.

II. Background

A. Rainfall and credit supply

We have remarked above that rainfall and supply of credit are two key determinants of agricultural output in India. There is substantial evidence in the existing academic literature as well as professional reports and government policy papers that rainfall is an important determinant of Indian farm output. Using rainfall and crop yield data for a panel of 272 districts over 32 years, Cole *et al* (2009) report a strong positive relationship between rainfall and agricultural output. On an average, one standard deviation increase in rainfall results in a 3% -

4% increase in the value of output in their sample. There is also wide recognition of the importance of rainfall to agriculture and national income in different agencies of the government, policy forums, political parties, and think tanks. The sentiment extends to the popular press. The *Financial Express*, a major financial newspaper in India, carried the following item on August 24, 2009:

"Approximately 25% of the country is affected by drought and agricultural output is set to plummet this year. Lower income for rural workers will in turn be a huge drag on private consumption, an important driver of India's economic expansion." The drought in question affected 25% of the country and was associated with 29% below normal rainfall during the busy Kharif season (June - September) in 2009.

The importance of agricultural credit, the other key determinant of farm output in India, is inherently tied to the heavy dependence of agriculture on rainfall. With the intermittent failure of the monsoons and other vicissitudes, farming in India has traditionally been a high-risk activity, resulting in high cost of credit and pervasive rural indebtedness (Mohan, 2006). We have observed before that ours is the first systematic study to link supply of agricultural credit to poor rainfall. However, from time to time the financial press and other media outlets in India report isolated instances of the effect of poor rainfall on bank credit availability. The same issue of the *Financial Express* cited above carried the following report:

"Taking special measures on behalf of the banking industry, Bank of Maharashtra chairman and managing director Allen CA Pareira said the bank is working on rescheduling agricultural loans for the affected farmers by converting the short-term loans to long-term ones. Normally the bank provides crop loans with the repayment period of a year only. However, we are trying to reschedule those loans so that farmers can repay them over a period of 3-5 years, he added." The same newspaper article also reported that the Bank of India, a big public sector bank, had planned to disburse Rs. 203 billion in farm loans instead of the usual Rs. 165 billion in the year.

B. Government initiatives

Given the importance of agricultural credit to farming in India, development of cost-effective rural credit systems has been a top priority of the Indian government for over a century. Over the years, it has set up multiple committees/working groups/task forces to recommend solutions[3]. The solutions have been broadly of three types: supply of agricultural credit through nationalized public-sector banks, requiring both public and private banks to extend at least a certain percentage of credit to agriculture and small-scale industry under a national priority sector lending scheme, and requiring all commercial banks to open four branches in an unbanked location for every new branch opened in a location with an existing bank. Since 1985, commercial banks have been required to lend a fraction of their total credit to the "priority sectors" defined by the government. Currently, the figure is 40% for domestic banks and 32% for foreign banks[4]. Of the priority sector lending targets for domestic banks, almost half (18% of total bank credit) is required to be directed towards agriculture. Foreign banks do not have specific targets for agriculture, presumably due to their minimal presence in rural areas.

There is documented evidence that the increase in rural credit supply owing to the redistributive nature of branch expansion has led to a significant decline in poverty among India's rural population (see Burgess and Pande, 2005; Burgess, Pande, and Wong, 2005). However, there have been few systematic studies of the effect of additional credit on farm output in India, except for Binswagner and Khandker (1992). They find that India's government-led approach to agricultural credit paid off in non-farm growth, employment, and rural wages, but the direct impact of expanded credit on agricultural output has been modest. However, in government reports, policy papers, and media reports a positive association between farm output and credit is often assumed.

C. Bank ownership in India

India has witnessed two waves of bank nationalization, first in 1969 and subsequently in 1980. On both occasions private banks, 14 in 1969 and 6 in 1980, with an all-India deposit base above a given threshold were compulsorily nationalized. The rationale for nationalization was that public banks could better serve rural and underbanked regions; they would promote an equitable distribution of credit, and would better serve sensitive sectors of the economy primarily

[3] The list of recent committees include "The High-level Committee on Agricultural Credit through Commercial Banks" (1998), "Task Force to Study the Functions of Cooperative Credit System and to Suggest Measures for its Strengthening" (1999), "Expert Committee on Rural Credit" (2001), and "The Working Group to Suggest Amendments in the Regional Rural Banks Act, 1976" (2002).

[4] Master Circular-Lending to Priority Sector, Reserve Bank of India, July 1, 2011

agriculture. Cole (2009b) finds that the nationalization did achieve development lending goals but had no impact on the real economy.

The arguments against nationalization focus on the soft incentives given to bank loan officers to extend loans to underbanked sectors and regions as well as their susceptibility to political capture. Using a sample of bank loans from a large public sector bank, Banerjee and Duflo (2008) finds evidence of the former. Bank officers are reluctant to lend to the optimal level, since the benefits for them from extending new loans are outweighed by the costs of potential corruption charges if the loans go bad. Cole (2009a) finds evidence that Indian public sector banks are susceptible to political capture. Agricultural credit goes through cycles where the peak occurs just before state elections.

As of March 31, 2010 (the date on which our sample ends), 27 public sector banks, 22 domestic private banks, and 34 foreign banks were operating in India. Regional rural banks (RRBs), a special category of banks set up in 1975 with the stated purpose of providing sufficient credit to agriculture and other sectors important to the rural economy, numbered 82 in total (RBI 2011). The Central Government owns 50% of each RRB, the relevant State Government owns 15%, and the remaining 35% is owned by a commercial bank which is known as the sponsor bank. Since our primary interest in this paper is in agricultural lending, it is instructive to note the share of agricultural credit originating from different bank groups. The share of foreign banks in direct agricultural credit is negligible since they do not have a significant rural network, nor do they face a mandatory lending requirement to agriculture unlike other bank groups. Of all the direct agricultural credit outstanding in India at the end of the 2009-2010 fiscal year, 73.1% came from public sector banks. RRBs had the next highest share with 14.4% while domestic private banks contributed 12.4%. The above figures show that banking in India, particularly rural India, is still heavily dominated by government-owned banks.

D. Bank regulator's initiatives

In addition to various attempts by the government to improve the rural credit supply situation in general, the central bank of India which also doubles up as the regulator of the banking sector has taken steps to exhort commercial banks to provide loan relief measures to the farmers following natural calamities. The Rural Planning and Credit Department (RPCD) of the Reserve Bank of India (RBI) issues annual guidelines to the commercial banks on loan relief measures to be provided in areas affected by natural calamities. The guidelines are issued in the form of an official circular. From time to time the existing guidelines are revised. Starting in 1984, five such major revisions have taken place (in 84, 91, 93, 98 and 2005).

The guidelines specify droughts, floods, cyclones, tidal waves and other similar calamities as natural calamities. Though the guidelines call on the banks to grant fresh agricultural loans as well as revise the terms of the existing loans, they typically leave the actual decisions, including the quantum of fresh loans and the revised terms for the old loans, to the discretion of the banks themselves. For the personal or consumption loans, the guidelines usually suggest a target. For example, the 2005 circular suggests that the banks may extend general consumption loans up to INR 1,000 to eligible persons in calamity-affected areas. The amount suggested has increased from circular to circular. But here too the guidelines offer only exhortations and fall short of imposing any mandatory requirements on the banks.

Our investigations reported in section VIII below indicate that the periodic revisions of the guidelines by the central bank have had little impact on agricultural credit supply following a drought in the countryside, though personal loans appear to have gone up. If the circulars influenced the banks' decision to extend more agricultural credit, then we would observe an increase in rural credit in the years following the issue of a new set of guidelines compared to the previous years. We investigate this issue with the 1998 and 2005 circulars, and find no such increase.

III. Hypotheses

The central question of this paper is the responsiveness of the commercial banks in India to exogenous credit demand shocks caused by poor rainfall. Our focus on credit from commercial banks to the exclusion of all other sources of rural credit does not result in loss of generality, because commercial banks are by far the most dominant source of formal credit to rural households (Basu and Srivastava, 2005)[5].

Given our topic, identification of demand and supply of credit is of paramount importance. All observed loan amounts are equilibrium values, equating and supply. How do we ascertain that the observed credit increases, if any, are supply-driven, and not demand-

[5] Using data from the Rural Finance Access Survey (RFAS) 2003 conducted by The World Bank, they note that commercial banks are the source for more than 80% of the formal credit outstanding in rural areas.

driven? We proceed on the reasonable and conservative assumption that rural credit demand exceeds, or at least matches, credit supply in a difficult year when personal savings are likely be depleted. In other words, we rule out the possibility of excess supply which would imply that the banks in our sample were inclined to offer more credit than demanded. If they were indeed so inclined, the test results would understate the true effects of increased demand on supply availability, and would be biased against our hypothesis.

As we have mentioned above, in a year of poor rainfall, the ability of the average farmer to pay off their current agricultural debt is diminished, but they still need a fresh loan for the next planting season. In our model, presented in the appendix, there are two types of farmers in a district: good and bad. The former achieve higher productivity per unit of land in all states of nature. In a drought-affected year, the farmers that are observed to pay off their current loans are all good type. They are given a new loan by their bankers. As a result, the level of their outstanding credit remains the same as before. The farmers that are unable to pay off their loans include the remaining good type farmers and all bad type. The bankers face a penalty if they recognize a bad loan, and therefore prefer to bailout the farmers that default on their current loans and give them fresh loans too, increasing their outstanding credit. As a result, total outstanding credit for all farmers together is observed to increase. In many cases, bailouts substitute a probability of a bigger future default for the certainty of a smaller current default. But it is not so in the case of drought-driven defaults, because a year of drought is typically followed by a year of normal rainfall. In our sample, given that a district had a drought in year t, in 15.3% cases it experiences a drought in year t+1 as well. In the whole sample, a drought occurs in 11% of all district-years. By an alternative measure of drought, if a district has a drought in year t, in 16.3% cases it again has a drought in year t+1. In the whole sample, drought occurs in 17.5% of all district-years.

From the discussion above, our model offers the following testable prediction and a difference-in-difference test:

H1: *The amount of agricultural credit outstanding in a district is higher following a drought-affected year compared to other districts not affected by the drought and also compared to other years without a drought.*

Our data of bank loans are obtained from *Basic Statistical Returns* (BSR) compiled annually by the Reserve Bank of India (RBI). The data includes outstanding bank credit for each occupation in each district in a given year, but not flow of credit in the year. An observed increase in outstanding credit could arise from one or both of two factors: (a) pro-borrower action taken by the banks, such as sanction of new loans and (b) acceptance of non-payment of interest and other dues on old loans in default which are added to the old loans until the loans are treated as non-performing and written off. The first factor implies that the banks actively help out rural borrowers in especially difficult times, whereas the second factor indicates that they passively evergreen existing loans. Does the second factor contribute significantly to observed increases in credit, if any? Lacking direct data on the two sources of credit, we are able to investigate this issue indirectly. If outstanding agricultural credit increases primarily because of late payment or non-payment of debt service charges in drought-affected years, other types of bank credit, especially personal loans, are also likely to register an increase in the same years. Actually, in their case the observed increase is likely to be higher. It should be noted that, unlike agricultural credit, personal loans are not included in priority sector loans and carry a considerably higher rate of interest than the controlled rates on priority sector loans. If outstanding personal loans are not observed to increase, then one could reasonably infer that the second source does not contribute significantly to the level of outstanding agricultural credit.

H2: *The increase in agricultural credit outstanding following a drought-affected year is due to new loans rather than to non-payment or delayed payment of debt service charges on existing loans.*

There is also another interesting way to test if late payment or non-payment of debt service charges causes the rise, if any, in agricultural credit outstanding following a drought. If this were indeed the case, then in districts which experience frequent droughts we would ex-ante expect bank managers not to renew loans from farmers which carry the risk of non-payment. In other words, the observed increase in agricultural credit following a drought would be proportionately less in a drought-prone district than in other districts. On the other hand, if the increase in outstanding agricultural credit in drought-prone districts proves to be similar to other districts, it would suggest that non-payment of debt service charges is not pushing up the volume of outstanding agricultural credit.

H3: *Following a drought, drought-prone districts experience a similar increase in agricultural credit than districts that are not drought-prone.*

Our model predicts that the credit increase will occur in the intensive margin (the average size of the existing loans) rather than in the extensive margin (the number of loan accounts). The prediction follows from the observation that the banks typically have more information about the type of their current borrowers than about new borrowers. Following a difficult year their information set is more refined, and they are better able to target better farmers within their current pool of borrowers for more credit. The information gain enables them to make better credit decisions.

H4: *The credit increase occurs in the intensive margin (the average size of the existing loans) rather than in the extensive margin (the number of loan accounts).*

We have noted in the previous section that the rationale offered for bank nationalization in India included the argument that public banks would better serve rural and underbanked regions and sensitive sectors of the economy, primarily agriculture. We have also noted that the government as well as the RBI periodically exhorts the banks to extend credit during droughts. The ownership pattern of public banks would seem to make them more susceptible to such interventions. Given the rationale behind bank nationalization, ours is an ideal setting to test whether nationalized banks serve the rural economy adequately, and whether private banks lag behind public banks in this regard. This leads to the fifth hypothesis of the paper:

H5*: The volume of agricultural credit extended by public sector banks in a district following a drought exceeds the corresponding credit extended by private banks*.

A prediction of our model provides the alternative hypothesis to H5. As we have discussed above, bank managers with both public sector and private sector banks have an incentive to bail out a farmer facing default and not recognize a non-performing loan. However, public sector bank managers typically lack proper incentives to provide additional loans to borrowers who are proven to be good and do not default on their current loans. Based on a sample of bank loans from a large public sector bank, Banerjee, Cole and Duflo (2005) argue that public sector banks in India are extremely inertia-prone, and attribute this to lack of proper incentives for public sector bank loan officers[6]. They face the threat of vigilance action if loans approved by them go bad, but are not rewarded commensurately if the loans perform well. We extend this argument and claim that private sector banks, by contrast, are more inclined to provide additional credit to good farmers. As a result, private banks are observed to respond more positively than public banks to combined credit demand from farmers of all types.

As we have remarked in the previous section of this paper, public sector banks are presumed to be vulnerable to political capture, and their loans can be controlled in ways that many other government expenditures, such as construction projects, cannot. This literature links government-controlled provision of bank credit to electoral goals. The Indian political system provides for exogenous election cycles which are different for different states. This variation can be exploited to test for joint effects of elections and droughts on agricultural credit supply. If agricultural credit in India, which should be allocated on commercial merit, is observed to increase in a district in an election year immediately following a drought in that district, compared to other drought-affected years, after controlling for the effect of the drought itself, the evidence would lend support to the hypothesis of political control of credit extended by public sector banks. The investigation suggests a difference-in-difference-in-difference test of the following hypothesis:

H6: *Agricultural credit supply is higher in a district when a drought precedes a state election than when it does not.*

IV. Data

The geographic unit in our analysis is the administrative district, similar to a county in the USA. According to the latest (2011) census, India has 640 districts spread across 28 states and 7 Union Territories. The largest state, Uttar Pradesh, has 72 districts while the state of Goa has only 2.

A. Bank Credit

Our data on bank credit comes from the Reserve Bank of India's annual publication '*Basic Statistical Returns of Scheduled Commercial Banks (BSR)*'. The publication provides data on the amount of credit outstanding, occupation-wise, as well as the number of accounts for

[6] The sample of bank loans in Banerjee, Cole and Duflo (2005) does not include agricultural loans.

which credit is outstanding, in each district at the end of the fiscal year (March 31 in the case of India). We have this data from 1993-94 to 2009-10. The data for agricultural lending is divided into two types: direct and indirect. Loans given to individual farmers come under the purview of direct agricultural finance. Indirect agricultural finance covers loans given to corporate food and agro-processing units as well as loans given to non-banking financial institutions for onward lending to farmers. Since our focus is on the effect drought has on farmers' demand for credit, and the response of the banks to this demand, we use the data for direct agricultural finance in our tests.

Table 1A provides the summary statistics of the bank credit variables in our sample. Almost 23% of the total credit outstanding for the median district-year observation is direct agricultural credit. There are almost 29,000 accounts with direct agricultural credit outstanding in the median district-year. These accounts tend to be small, with the median account having an outstanding amount of INR 24,500 (approximately USD 490 at the prevailing exchange rates)[7].

Table 1A here

B. Rainfall

Our data on rainfall and drought comes from the India Meteorological Department (IMD). We use the Standardized Precipitation Index (SPI) as our primary measure of drought conditions. The SPI is a drought index developed in McKee, Doesken and Kleist (1993). It is based on the probability of observing a given amount of rainfall in a particular year. The SPI for a year registering the median rainfall is zero. The deviation from the median is standardized to arrive at the index value for a particular year. We obtain SPI data for Indian districts from a study by Pai, Sridhar, Guhathakurta and Hatwar (2010). It computes the SPI for India's main monsoon season, namely the Southwest monsoon season, for 458 districts for the period 1901-2003. The Southwest monsoon season lasts from June to September. As mentioned in Pai et al (2010), if the SPI measure for a district in a given year is less than -1, the district is said to be suffering from a moderate drought. We code all such instances as drought observations for our sample of SPI indices (1993 -2003).

We also construct an alternative measure of drought, using the percentage of normal (PN) method. In this method, the rainfall in a particular year is compared to the district's long period

[7] In Nov 2011, the exchange rate was approximately 1 USD = 50 INR

average (LPA) rainfall. If the rainfall is less than a certain percentage of the LPA, the district is said to be suffering from a drought. Pai et al (2010) suggests 75% of LPA as the cut-off below which a district is considered to experience a moderate drought. This is the yardstick we use[8]. Annual rainfall data at the district level from 1993 onwards in obtained from the National Data Centre (NDC) at the IMD. We obtain data on the LPA from the IndiaStat database. IndiaStat collects its data from different sources. For many of the districts, two or three different values of the LPA are available. We only calculate the PN measure for those districts for which we have a consensus LPA or those where the difference between the highest and lowest estimate of LPA is not more than 5% of the lowest estimate[9]. This exercise reduces the number of districts for which we are able to calculate PN measures to 334. We have no reason to believe that the exercise introduces non-randomness into our districts data.

The summary statistics of the weather variables are reported in Table 1B. Since our bank credit data starts from 1993-94, we report the weather variables from 1993-94. For the SPI measure, the median value is, as expected, close to 0. For 11% of the observations the value of SPI is less than -1, indicating drought.

Table 1B here

Over the period 1993-2010, the median district-year rainfall is 1014mm with a standard deviation of 838mm. The median district-year observation deviates from the LPA by only 0.3%. For 17.5% of the observations, the rainfall is less than 75% of the LPA, implying drought conditions. Among our two measures, PN reports drought with a significantly higher frequency than SPI. One potential reason, apart from difference in measurement methods, is the fact that the data periods are different. If we look only at those years for which we have both SPI and PN values, we find that drought incidence using PN reduces to 16.3%. However, this is still significantly higher than the drought incidence using SPI (11%). Figure 1 below plots drought frequency using both measures.

Figure 1 here

C. Other data

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[8] We also run our tests with a threshold of 70% of LPA and 80% of LPA. Results do not change significantly.

[9] As a robustness check, we also drop those districts where the difference between the highest and lowest estimate of LPA is more than 2.5%. The results are largely similar.

In order to test the third hypothesis discussed above, it is necessary to identify the drought-prone districts in India. We obtained a list of 99 drought-prone districts from the Compendium of Environment Statistics, 2002, released by the Central Statistical Organization, Government of India[10]. Figure 2 below maps the distribution of the drought-prone districts. Not surprisingly, the drought-prone districts are concentrated in the arid regions of western and north-western India as well as the Deccan plateau. However, the 99 drought-prone districts are spread over as many as 15 states.

Figure 2 here

The last hypothesis discussed above focuses on the role of election cycles in bank credit disbursement. To test the hypothesis we focus on elections to state legislative assemblies since national elections would get subsumed by year fixed effects in our regression models. Each legislative assembly has a term of five years, though elections might be held earlier if the government loses its majority in the assembly. However, the states hold elections in different years and months, generating variation in the data which we exploit. Our data on election dates comes from the website of the Election Commission of India, a constitutional authority responsible for the conduct of all national and state elections.

We also test whether government response to droughts interacts meaningfully with the response of the banking system. Real per capita non-plan expenditure of state governments on relief on account of natural calamities is our measure of government response. This proxy has been used in other studies that examine government responsiveness to natural calamities in India, such as Besley and Burgess (2002) and Cole, Healy and Werker (2012). The calamities include droughts, floods, cyclones, earthquakes etc. The relief amount separately for droughts is not available. The nominal amounts of expenditure are obtained from the RBI's Handbook of State Government Finances[11]. We calculate state GDP deflator using state GDP data from the Central Statistical Organization, and obtain. state-wise population data from the Census of India website.

We also attempted to collect data on state governments' expenditure on debt relief for farmers. It is included in what the state governments report in their budget as their expenditure

[10] The IndiaStat database also reports the list.

[11] The state governments in India follow a standard budget format. They report their expenditure on relief for calamities under "major" budget head 2245. The RBI compiles the data for all states.

on social security and welfare[12]. We sought the data on debt relief for farmers from the governments of all the 28 states and 7 union territories in India, using petitions under the Right to Information (RTI) Act, 2005. While an encouraging number of state governments (23 out of 28) and 2 union territory governments responded to our queries, several of the responses did not provide the information we sought. However, none of the state governments acknowledged having provided debt relief for farmers within our sample period. The responses were uniform in this respect.[13]

V. Results: Agricultural Credit and Drought

We present our results in three parts. This section outlines the empirical strategy we use and present the results of the tests of the first four hypotheses. It may be recalled that the hypotheses verify in different ways the response of the commercial banking system to drought-induced shocks to demand for credit of the rural households in Indian districts. In the next two sections we present results of our investigations whether type of bank ownership and political economy of banking make a significant difference to the banks' response.

A. basic test model

The regression model in (1) below is the basic regression model of our study. It is used with appropriate modifications in all other tests of this paper.

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta OtherCredit_{dt} + \varepsilon_{dt} \quad (1)$$

Depending on the specification, $AgriCredit_{dt}$ in equation (1) is the volume of direct agricultural credit outstanding, or the ratio of direct agricultural credit to total bank credit outstanding, in district d at the end of the fiscal year t. The RBI defines the fiscal year t as the period from April 1 of calendar year $t-1$ to March 31 of year t. All our bank credit data are available for fiscal years, since *BSR* data compiled by the RBI is our main source for this data. However, all our rainfall data are available for calendar years. Since the main rainfall season is the southwest

[12] The state governments report their expenditure on social security and welfare under the "sub-major" budget head 2235.

[13] However, the central government of India launched a large-scale debt relief program for delinquent farmers, known as the Agricultural Debt Waiver and Debt Relief Scheme (ADWDRS), in February 2008, as part of the last central budget before the national elections in India. The relief covered overdue debt owed to commercial banks as of December, 2007. Notably, the ADWDRS program was not undertaken in response to rainfall shocks. The years preceding the program experienced normal annual rainfall and increasing food grains production. In particular, the year 2007 was a good year in terms of rainfall as well as agricultural production (De and Tantri, 2015).

monsoon season which lasts from June to September, poor rainfall in calendar year *t-1* is most relevant to agricultural credit at the end of fiscal year *t*.

Note that it is an economical model. The independent variable of interest is $Drought_{t1}$, a dummy taking the value 1 in drought-affected years and 0 in other years. The amount of rainfall in a particular district-year is an exogenous variable, and orthogonal to other district-wide factors that may affect credit supply. On running regressions of the drought dummy variables on both district and year fixed effects, we find that only a small fraction of the variation in the drought variable is explained by either set of fixed effects[14]. This suggests that there is significant variation in rainfall deficiency among districts in a particular year, as well as in a given district over time. These characteristics of $Drought_{t-1}$ variable imply that the co-efficient δ is a reliable difference in difference (DID) estimate of the effect of drought on agricultural credit. $OtherCredit_{dt}$ is the total amount of bank credit outstanding less direct agricultural credit in district d at the end of fiscal year t. We include this variable as a proxy for the development of the banking industry in the district. It also controls for the district's economic development in a particular year. The regression model includes district fixed effects, γ_d, to control for time-invariant cross-sectional variations in credit supply. Similarly, year fixed effects control for annual nation-wide macroeconomic fluctuations and other factors that may affect credit supply. In alternate specifications in place of year fixed effects we include region year fixed effects to control for annual regional fluctuations in credit supply unrelated to weather. Throughout, we cluster standard errors at the district level, and winsorize all data at the 1% level to eliminate outliers and data discrepancies.

B. Effect of drought on credit in a district

The most direct way to test our first hypothesis that the volume of agricultural credit outstanding in a district is higher following a drought-affected year is to compare the volume at the end of the year following a drought with other years. To that end we carry out a pooled OLS estimation of equation 1. The results are presented in Table 2 below.

Table 2 here

[14] In the case of annual rainfall, the variation explained by district fixed effects is quite large. However, year fixed effects again explains only a small fraction.

In Panel A, the dependent variable is the logged value of agricultural credit outstanding at the end of the fiscal year. In Panel B, the dependent variable is the ratio of the direct agricultural credit outstanding to the total bank credit outstanding. In this table, and all subsequent tables, we report results with both measures of drought: SPI based as well as PN based. As we have discussed before, the two measures are estimated using somewhat different methods. To control for the difference in measurement techniques, we construct a stricter measure of drought and report results for this measure. We create a dummy variable that takes value 1 if and only if both SPI and PN measures of drought are available for the district-year observation and both of them indicate that the district suffered a drought in that year. The variable is 0 if both measures are available and if at least one of them suggests that the district did not suffer a drought. The number of district-year observations applicable to the stricter measure of drought is of course less than when either of the two measures is used.

The results in both panels A and B of table 2 provide clear evidence supporting our first hypothesis. Agricultural credit outstanding is higher following a drought. In panel A, under both SPI (column 1 and 2) and PN based (column 3 and 4) measures of drought, we find that δ is positive and significant (except in column 4). The magnitude of the difference differs somewhat between the two measures of drought. Under SPI, the credit outstanding in drought-affected years is higher by about 4 – 5 percent (significant at 1% level), while it is about 3% higher and significant at 5% level in the case of the PN measure[15] in column 3. The results using the stricter measure of drought as our independent variable of interest are reported in columns 5 and 6 of the table. The reported coefficient in column 5 is of a much larger magnitude (9 percent, significant at 10% level). District-years where both measures of drought agree appear to signal a more severe drought. However, though positive, the coefficient is not significant in column 6.

With the ratio of agricultural to bank credit outstanding as the dependent variable (Panel B), the point estimates are positive and significant in all specifications, and very similar to the estimates using the logged value of agricultural credit: about 4% for the SPI-based measure (significant at 1% level), 3% for the PN-based measure (significant at 5% level), and 6% – 8% when both measures indicate a drought (again significant at 5% level).

[15] Since the dependent variable is logged, the co-efficient on Drought can be approximated as the percentage effect

A feature of these, and all subsequent results, is the very high value of adjusted R-square of the regressions (well over 0.9). The high value is driven, not surprisingly, by the inclusion of fixed effects. District fixed effects alone explain almost 75% of the variation in agricultural credit. Year fixed effects alone explain another 16%. The number of observations for regressions with SPI-measure and PN-measure of droughts are very similar (3296 and 3420). As we have remarked above, the SPI measures are available for more districts but for a shorter time period than PN measures. For the tests with both measures, the number of observations decline to 1414.

C. Effect in neighboring districts

To further confirm that the results we obtain are due to the effect of drought alone and not some other factors, we conduct a falsification test. We look at neighboring districts of drought-hit districts – the districts that share a physical border with the drought-hit districts - but do not experience a drought themselves. We run the same regression equation as equation (1), except that the dependent variable in this test is the average agricultural credit outstanding in neighboring districts of district *d* in fiscal year *t*[16]. We only include neighboring districts that did not experience a drought in calendar year t-1. The estimate of the co-efficient δ in this case indicates the percentage increase in agricultural credit outstanding in neighboring districts when district d is drought-hit compared to when it is not. We hypothesize that δ is insignificant, since the effect of the drought on district-level credit supply should be restricted to the district itself. Farming in India is a local activity, and with a widespread network of bank branches in the country[17], it is reasonable to expect the rural households to seek bank credit in the districts where they do the farming. The results in table 3 below confirm our hypothesis.

Table 3 here

Using the SPI measure (columns 1 and 2) as well as the combined measure (columns 5 and 6), the effect of a drought in a district on the agricultural credit in neighboring districts not affected by the drought is insignificant. Interestingly, when the PN measure is used, the effect is negative and significant. The average agricultural credit in neighboring districts comes down by almost 5% (significant at 1 – 5 percent level). This may indicate that the banks transfer loanable funds to drought-affected districts. Importantly, in no case is the effect positive and significant.

[16] We also do the test using the total agricultural credit in neighboring districts. The results are similar.
[17] Basu and Srivastava (2005) notes that the average population as well as area served per bank branch in India compares favorably with other developing countries.

Districts affected by a drought witness an increase in agricultural credit, but no such increase in observed in neighboring districts. This finding provides confirmation that the results reported in table 2 above are due to poor rainfall itself and not due to some unobserved time-varying regional/ geographic factors.

D. Dynamics of bank response

After having established that a drought has a statistically and economically significant effect on agricultural credit supply at the district level, we examine the dynamics of the effect[18], and test whether the effect is temporary or persists over time. In particular, if a drought is a truly exogenous event, then its effect should not be anticipated in advance. To test the dynamics, we estimate the following regression equation

$$AgriCred_{dt} = \alpha + \gamma_d + v_t + \delta_1 D_{dt-1}^{-6} + \delta_2 D_{dt-1}^{-5} + \ldots + \delta_{11} D_{dt-1}^{5} + \delta_{12} D_{dt-1}^{6} + \beta BankCred_{dt} + \varepsilon_{dt} \quad (2)$$

As in equation (1) before, $AgriCredit_{dt}$ is agricultural credit outstanding in district *d* at the end of the fiscal year *t*. The difference between equation (1) above and the present equation is that we drop the $Drought_{t-1}$ dummy variable and instead introduce a series of dummy variables where D^{-i} equals 1 for a district in the *i*th year before a drought and 0 otherwise, while D^{i} equals 1 in the *i*th year after a drought and 0 otherwise. Since we exclude the dummy for the year of the drought, we are able to estimate the dynamics relative to that year. As before, we include district fixed effects, year fixed effects or region-year fixed effects as well as the log of bank credit as a control, and cluster standard errors at the district level. The dummies at the end points, D_{dt-1}^{-6} and D_{dt-1}^{6}, refer to 6 years or further away from the drought year. Excessive variance in rainfalls in the end zones may make the estimates for those points less precise.

One complication in studying the dynamics is that a particular district might suffer multiple droughts over our sample period. If the droughts are close enough, the dynamic effects of one drought may interfere with the dynamics of another. To get around this problem, we conduct the analysis only for those districts which experienced a single drought in our entire sample period[19]. This leaves us with 42 districts using the SPI-based measure of drought, and 61 using PN-based measure.

[18] The analysis in this sub-section is in the spirit of the relevant section in Beck, Levine and Levkov (2010)

[19] We also exclude those districts for which we have less than 10 drought observations.

Figure 3 below plots the results with the 90% confidence intervals. Figure 3(a) portrays the results using SPI, while Figure 3(b) uses the PN measure of drought. Both graphs suggest the same conclusions. Both before and after a drought, the amount of agricultural credit outstanding is lower than that immediately following the drought. This result is much clearer in the case of Figure 3(b) which includes more districts as well as a longer time period (1993 – 2010). Though the confidence intervals in both figures are wide, we do see that the point estimates are below zero for almost the same years in both figures.

Figure 3 here

E. Active or passive response by banks?

In this sub-section, we discuss the results for our second hypothesis. The increase in agricultural credit outstanding could be caused by active borrower-friendly response of the banks to the drought (either by extending more credit or restructuring existing loans), or it could be simply due to passive acceptance by bankers of non-payment of debt charges on existing loans by the borrowers in a difficult year whereby the charges are added to the outstanding credit. Lacking direct data on fresh loans, we investigate this issue indirectly. To test which of the two reasons is more pertinent we look at non-agricultural credit, in particular personal loans. As we have discussed above, if outstanding agricultural credit increases primarily because of late payment or non-payment of debt service charges in drought-affected years, other types of bank credit, particularly personal loans, are also likely to register an increase in the same years, especially because non-agricultural loans, unlike agricultural credit, are not included in priority sector loans and carry a considerably higher rate of interest. On the other hand, if banks respond positively to the plight of the farmers following a drought, they would extend more agricultural credit but not more non-agricultural loans. Therefore, whether personal loans appear to increase or not provides a clue to the source of the increase in outstanding agricultural credit following a drought.

The above intuition calls for a series of tests. To start with, we estimate a modified equation (1') where other types of loans replace direct agricultural credit as the dependent variable but all other variables remain the same as (1) before :

$$OtherLoans_{dt} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta BankCredit_{dt} + \varepsilon_{dt} \quad (1')$$

Panel A of table 4a below presents the estimation results of equation (1') where the dependent variable is the logged value of personal loans outstanding in district *d* at time *t*. We use both PN-based and SPI-based drought measures, as well as the third measure representing the intersection of the two measures. Under all three specifications, the reported effect of droughts on outstanding personal loans is insignificant. In fact, the coefficient of SPI measure of drought has the wrong sign (negative). The finding lends support to our second hypothesis that the increase in agricultural credit is motivated by the positive borrower-friendly response of the banks to the drought. Panels B and C report the results with non-agricultural, non-personal credit and total bank credit respectively. In all specifications the effect of drought on the credit outstanding is insignificant panel B. However, in the case of total bank credit the point estimates are positive in all specifications, and significant for the third measure.

Table 4a here

However, one could argue that personal loans and other non-agricultural loans are taken mostly by non-farm workers whose repayment behavior might be quite different from that of the farmers faced with a drought. To check this possibility, we create a sub-sample of districts where the ratio of agricultural credit to total bank credit is higher than the national median. These are more rural districts where the importance of agriculture is high, and the proportion of non-farm workers is likely to be small. We estimate equation (1) for this sub-sample using both direct agricultural credit and personal loans as the dependent variable. The results, reported in Table 4b below, confirm the earlier results. Agricultural credit outstanding in these districts increases following a drought, but the amount of personal loans outstanding remains unaffected. Further, the coefficient estimates of the drought variables remain virtually the same as in the full sample, though the significance levels are lower because the number of observations are about half as before.

Table 4b here

A potential peril in comparing the outcomes for agricultural credit and personal loans is the possibility of strategic default on agricultural loans, but not on personal loans. State governments may waive agricultural loans by the following a drought. By contrast, personal loans are never waived. Given this background, might the farmers in drought-hit districts strategically default only on agricultural loans expecting to be bailed out by the government, but not default on personal loans? This selective strategic default could conceivably explain the increase in agricultural credit outstanding while leaving other credit unchanged. And the increase in this case would be due to addition of unpaid debt service charges, and not fresh loans. To address this issue, we investigate whether the amount of government debt relief extended in the wake of a previous drought in a district has a differential effect on the increase in agricultural credit outstanding following the current drought. If selective strategic default in anticipation of a loan waiver causes the observed increase in agricultural credit, we would expect the increase to be more pronounced in districts where government relief was higher following the previous drought experienced by the district.

Formally, we estimate the following regression equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * ReliefExpd_{st-k} + \zeta + \beta BankCredit_{dt} + \varepsilon_{dt} \qquad (3)$$

In equation (3), the coefficient δ_2 of the interaction term $Drought_{dt-1}*ReliefExpd_{st-k}$ is the coefficient of interest. $ReliefExpd_{st-k}$ is the amount of relief expenditure in state s in year $t-k$ where k refers to the number of years between successive droughts in district d. We attempt to estimate equation (3) using two different sets of government relief expenditure data. As we have mentioned in the data section above, we submitted petitions under the RTI Act, 2005, to obtain data on debt relief for farmers included in state annual budgets. None of the governments acknowledged having provided debt relief for farmers within our sample period. Therefore, the farmers in drought-affected districts in our sample could not have conditioned on past debt relief, nullifying the hypothesis of strategic default.

We obtained a second set of data, namely state government relief expenditure on account of natural calamities, from the Handbook of State Government Finances issued by the RBI. As we have discussed in the Data section above, this data has been used in other studies that examine government responsiveness to natural calamities in India, such as Besley and Burgess (2002) and Cole, Healy and Werker (2012). The calamities include droughts, floods, cyclones, earthquakes etc. The relief amount separately for droughts is not available. Another issue with this data is that it is available only at the state-year level; data at the district level is not available. In our tests we use the data deflated by the state GDP deflator.

The results of the pooled OLS estimation of equation (3) are reported in table 4c below. In all specifications, using either drought measure, the coefficient δ_2 is insignificant. The finding suggests that the increase in agricultural credit in a drought-hit district is unrelated to the amount of relief expenditure in that state during the previous drought in that district. If farmers were selectively defaulting on agricultural loans, we would expect the increase in agricultural credit to be higher when the relief expenditure during the previous drought was higher. The test results with the second set of data again rule out strategic default by farmers as an explanation for the observed increase in agricultural credit.

The table indicates that the number of observations used for this test is sharply lower: 1,364 for the SPI-based measure and 1,613 for the PN-based measure. This is because for many droughts in our sample the previous droughts are outside the sample period.

Table 4c here

F. Is the effect different in drought-prone districts?

Our third hypothesis compares the effect of drought in drought-prone districts and non drought-prone districts. Our source for the list of drought-prone districts is the Compendium of Environment Statistics, 2002, released by the Central Statistical Organization, Government of India. The list includes a total of 99 districts. Not surprisingly, the drought-prone districts are concentrated in the arid regions of western and north-western India, though they are spread over 15 states.

To formally test our third hypothesis, we use the following equation:

$$AgriCred_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * Drought\text{-}Prone_d + \beta BankCred_{dt} + \varepsilon_{dt} \quad (4)$$

The equation is the same as equation (1) in all respects except that it adds an additional variable interacting the drought variable with $Drought\text{-}Prone_d$, a dummy variable that takes the value of 1 for the 99 drought-prone districts, and 0 otherwise. The coefficient of the variable δ_2 is of interest here. While δ_1 measures the effect of drought on agricultural credit in non drought-prone districts, δ_2 measures the differential effect in districts that are drought-prone. $\delta_1 + \delta_2$ measures the combined effect in drought-prone districts. Table 5 below presents our results.

Table 5 here

Panel A of Table reports the results of the pooled OLS estimation of equation (4) for the full sample. In both column 1 and 2, the coefficient on the drought variable is positive and significant as before. However, the coefficient on the interaction term is insignificant in both cases. The tests do not find evidence that the effect of drought on agricultural credit is different in drought-prone and non drought-prone districts. Next, we split our sample into two parts, one includes drought-prone districts and the other does not. We estimate equation (1) separately for these two sub-samples. In panel B of the table, we report the results for the drought-prone district sample. The estimate of the drought coefficient is positive but insignificant. This might be due to the low number of observations we have for the drought-prone districts sample: 753 for the SPI-based measure and 728 for the PN-based measure. For the non drought-prone districts, the results for the drought coefficients are very similar to the results for the full sample in panel A.

The results support our third hypothesis. We do not find any evidence that the effect of drought on agricultural credit outstanding is different between drought-prone districts and other districts. These results also lend further credence to our second hypothesis. If late payment caused the rise in agricultural credit outstanding, then in districts which experience frequent droughts we would ex ante expect bank managers not to renew loans to farmers who, judging by their past records, run the risk of non-payment. As a result, outstanding agricultural credit would increase proportionately less in drought-prone districts than in others. Our findings do not support this implication.

G. Intensive or extensive margin?

So far our test results indicate that agricultural credit extended by commercial banks in a district increases following a drought, and that the increase appears to be driven by fresh loans rather than non-payment of debt service charges on old loans. Is the increase in credit due to an increase in the number of accounts, or to an increase in the amount of credit outstanding in the average account? Since we have data on the total number of accounts in a district which have credit outstanding at the end of a year, we are able to determine the credit outstanding in the average account.

We estimate equation (1) by pooled OLS again, but change the dependent variable to number of accounts or average account size as the case may be. The results of the estimation are presented in Table 6 below.

Table 6 here

Panel A of the table reports the results where the dependent variable is the logged number of agricultural credit accounts outstanding. The point estimates are positive but statistically insignificant in all cases. In Panel B, the logged value of the average amount of agricultural credit outstanding is the dependent variable. The coefficients of all drought variables are positive and significant in all specifications. The increase in the average account size ranges from 2.2 to 3.4 percent when we measure drought using either SPI or PN. For our combined measure, which counts a drought only when both SPI and PN measures indicate a drought, we find the effect to be significantly larger – of the order of 9 percent. The results of both panels taken together clearly suggest that the increase in agricultural credit outstanding following a drought is driven by an increase in the average amount in an account rather than an increase in the number of accounts.

VI. Results: Does bank ownership make a difference?

We have seen above that the Indian banking sector, as a whole, is responsive to increases in demand for agricultural credit following a drought. We now examine whether private and public banks differ in their response and test hypothesis H5.

As we have mentioned in the data section before, we obtained the annual data for agricultural credit outstanding at the district level by bank ownership group for the period 2001-2010 from the *Department of Statistics and Information Management* of the RBI. We organized the data into three broad groups: all public banks, all private banks (including foreign banks) and regional rural banks (RRBs).

Our empirical strategy remains essentially unchanged. The regession model we estimate is:

$$AgriCredit_{dtb} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta_1 OtherCredit_{dtb} + \beta_2 Area_{dt} + \varepsilon_{dt} \tag{5}$$

The main difference from regression model (1) is that the credit variables now indicate credit for district *d* in year *t* given by banks belonging to ownership group *b*. There is also a new control variable $Area_{dt}$, indicating area under cultivation in a district-year. As indicated in the data section above, the data for this variable is available only since 1998. The estimation results for equation (5) are presented in Table 7 below.

Table 7 here

The reported results are for PN-based measure of drought only, since SPI-based measures of drought are available only up to year 2003. Panel A of the table presents the results for all banks, panel B for public sector banks, panel C for RRBs and panel D for private banks. As discussed above, the presence of foreign banks is minimal in rural areas during our sample period. In order to avoid sample selection problems, in our test sample we include only those district-years where all three bank types are present. This drastically reduces our sample size to 1,431 observations. From the table, all banks increase credit by 4% in response to a drought. This result is comparable to the result for the full sample period 1993 - 2010 (3.4% from column 3 in table 2 before). Public sector banks also increase agricultural credit by 4.3% in response to a drought. The results are statistically significant at 5% level. . The RRBs and private banks do not appear to increase credit at all. However, the results are consistent with the null hypothesis that public sector banks respond more effectively to sudden credit demand shocks in the rural sector.

Area under cultivation appears to have a strong and significant effect on credit supply by public sector banks (12% with p-value of 0), but not the other banks. The results make sense. Farmers usually get agricultural loans form public sector banks. Land under cultivation and crop standing on the land are typically pledged as collateral for farm loans.

VII. Results: Political Economy of Bank Response to Droughts

In this section we investigate whether political economy issues influence the provision of bank credit following a drought and, if so, how. We test hypothesis H6 which focuses on the role of elections in provision of bank credit. We also examine if and how the government response to droughts interacts with the response of the commercial banks.

A. Droughts, elections, and bank credit

Does direct agricultural credit increase more if the drought happens just before an election? To test the hypothesis, we focus on elections to state legislative assemblies. Each legislative assembly has a term of five years, though elections might be held earlier if the government loses its majority. Importantly, Indian state elections are not synchronized, making it possible to exploit the variation in the relationship between the electoral cycles and credit cycles, while ruling out the possibility of macroeconomic fluctuations as an explanation for the variation. Elections in India generally take place between October and May (i.e. after the southwest monsoon season ends). Our data on election dates comes from the website of the Election Commission of India, a constitutional authority responsible for the conduct of all national and state elections.

To test the hypothesis, we estimate the following equation:

$$AgriCred_{dt}=\alpha+\gamma_d+\nu_t+\delta_1 Drought_{dt-1}+\delta_2 Drought_{dt-1}*Election_{st}+\zeta Election_{st}+\beta BankCred_{dt}+\varepsilon_{dt} \quad (6)$$

The variable $Election_{st}$ takes the value 1 if state s has an election in the period from October of year $t-1$ to September of year t (i.e. twelve months immediately following the monsoon). We construct a variable $Drought_{dt-1}*Election_{st}$ which has the value 1 if a district suffered a drought in year $t-1$and also had a state assembly election right after the drought. The coefficient of this variable is our coefficient of interest. As a robustness test, we also test for the impact if the election is scheduled a year later (in year t+1). The regression model includes $\zeta Election_{st}$ to control for the effect the election cycle itself has on agricultural credit.

The results of the pooled OLS estimation of equation (6) are presented in Panel A of Table 8a. We find similar results with both measures of drought. The coefficients of *Drought (SPI)*, 0.051, and *Drought (PN)*, 0.021, are very similar to the regression model without the interaction terms with election (see columns 2 and 4 of table 2 before). The coefficient of the interaction term with *SPI* measure is negative and statistically significant at 5%, while the coefficient of the interaction term with *PN* measure is 0. We do not find any evidence to suggest that agricultural credit increases more following a drought which occurs just before an election compared to other droughts. The drought variable by itself continues to explain the observed variation in agricultural credit outstanding. Interestingly, the coefficient of the election variable is positive for both measures, but significant only for the *PN* measure. Taken together, the results indicate that credit supply increases in election years, but do not increase further if droughts precede the election years. Overall, the results are consistent with Cole (2009).

Table 8a here

Next, we divide our sample into two parts – one with election years only and the other without. We estimate equation (1) separately for these two sub-samples. The results are reported in Panels B and C respectively. We find that the point estimate of the impact of drought on agricultural credit in election years is negative by *SPI* measure and positive by *PN* measure. However, the estimates are statistically insignificant, and the number of observations is low (716 and 768 respectively). The results for the sample without election years, with many more observations, are very similar to the full sample.

B. Droughts, elections, and credit by bank ownership type

Does bank ownership make a difference to our findings in the sub-section above? To test the hypothesis, we estimate the following equation:

$$AgriCred_{dtb}=\alpha+\gamma_d+\nu_t+\delta_1 Drought_{dt-1}+\delta_2 Drought_{dt-1}*Election_{st}+\zeta Election_{st}+\beta BankCred_{dtb}+\varepsilon_{dt} \quad (7)$$

The only difference from regression model (6) above is that the credit variables indicate credit for district *d* in year *t* given by banks belonging to ownership group *b*. The estimation results for equation (7) are presented in Table 8b below.

Table 8b here

The reported results are for PN-based measure of drought only, since SPI-based measures of drought are available only up to year 2003. As in table 7 before, panel A of the table presents the results for all banks together, panel B for public sector banks, panel C for RRBs and panel D for private banks. The coefficient of *Drought (PN)* is positive and significant for public sector banks, but insignificant for the other bank groups. The coefficient of the interaction term $Drought_{dt-1}*Election_{st}$, is insignificant for all bank group. However, the coefficient of the *Election Year* itself is positive for all bank groups, and almost significant for public sector banks (3%, p-value .11). In election years, all bank groups appear to increase their lending to rural households, though credit supply does not appear to increase further in election years following a drought. This confirms our conclusions from the results in table 8a above.

C. Interaction between bank response and government action

A natural source of relief following a drought would be the government. Besley and Burgess (2002) and Cole, Healy and Werker (2012) are among the papers that study how state governments respond to natural calamities in India. In this paper, we focus on if and how the government response to droughts interacts with the response of banks. Are the two responses complementary – do responsive governments prevail upon banks, particularly public sector banks, to increase lending to drought-hit areas? Or is bank responsiveness a substitute for government responsiveness – if governments do not respond, because of incompetence, inertia or fiscal constraints, do banks step in? We attempt to answer these questions by estimating the following regression equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * ReliefExpd_{st} + \zeta + \beta BankCredit_{dt} + \varepsilon_{dt} \quad (8)$$

In equation (8), the coefficient on the interaction term $Drought_{dt-1} * ReliefExpd_{st}$ is the coefficient of interest. As discussed earlier, data on relief expenditure on account of natural calamities is obtained from the Reserve Bank of India's Handbook of State Government Finances. We have this data only at the state-year level; data at the district level is not available. We use the data deflated by the state GDP deflator.

The regression estimates are presented in Tables 9a and 9b. Table 9a presents results using both measures of drought for the full sample period. The coefficient of the interaction term $Drought_{dt-1} * ReliefExpd_{st}$ with the SPI-based measure of drought is negative which would imply substitutability. On the other hand, the coefficient of the interaction term with the PN-based measure of drought is positive, indicating a complementary relationship. However, both coefficients are statistically insignificant. Taken together, the results do not provide a clear picture whether bank response and government response are complements or substitutes. They appear independent of each other. The coefficients of the two drought variables, as well as that of the third measure which records a drought only when the other two measures also signal drought, are all insignificant.

Table 9a here

In table 9b we present the results for the four bank groups separately. Panel A of the table presents the results for all banks together, panel B for public sector banks, panel C for RRBs and panel D for private banks. The results are available only for the PN-based measure of drought for the period 2001-2010. The coefficient of the interaction term $Drought_{dt-1} * ReliefExpd_{st}$ is insignificant for each group. Again the results suggest that the commercial banking system and the government respond to droughts independently of each other.

Table 9b here

VIII. Do RBI circulars influence bank behavior?

In Section II above, we noted that the Reserve Bank of India issues annual guidelines to banks on providing relief for farmers facing natural calamities. In this section, we briefly investigate whether these guidelines influence bank lending behavior in the rural sector. As mentioned earlier, these guidelines have undergone five major changes (in 84, 91, 93, 98 and 2005). The first two are not covered by our sample period, while the third is in the first year of the sample. Hence, we focus on the implications of the changes of 1998 and 2005. Our empirical strategy is straightforward. We test whether agricultural credit extended following a drought is different in the years preceding and following a change in guidelines. Formally, we estimate the following regression equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1}*Post_T + \beta BankCredit_{dt} + \varepsilon_{dt} \quad (9)$$

The coefficient δ_2 of the interaction term $Drought_{dt-1}*Post_{T.}$ is our coefficient of interest. The variable $Post_T$ takes the value 1 in years after T and 0 otherwise. We are interested in the cases where T is 1998 and 2005. Panel A of Table 10 reports the results of the estimation of equation (9) when T is 1998. The coefficients of the interaction term $Drought_{dt-1}*Post_{1998}$ is insignificant in all specifications, including *Drought (SPI), Drought (PN) and Drought (combined SPI and PN)*. The results suggest that the changes in the RBI guidelines exhorting banks to lend more to farmers in tough times had no incremental impact on agricultural credit, either positive or negative. In unreported results, we find similar results when T is 2005. In that case, the only measure of drought we have is the PN measure (since SPI data is available only till 2003).

We have noted in section II above that the RBI guidelines also ask banks to increase personal and consumption loans. Panel B of Table 10 uses volume of personal loans instead of agricultural credit as the dependent variable. Here also the coefficients of the drought variables and the interaction terms are all insignificant. One must recognize, however, that the results in this section need to be interpreted with more caution than our other results, since the observed insignificant effects could also be driven by confounding time-varying factors unrelated to the change in the RBI guidelines.

IX. Conclusions

This paper presents evidence that commercial banks in India respond to droughts by increasing direct agricultural credit to the rural households. The increase is driven by an increase in average account size rather than an increase in the number of accounts, and is not different for districts which experience frequent droughts. We do not find any evidence that the increase is motivated by political considerations – the point at which the drought occurs in the election cycle has no bearing on the credit extended. The increase also does not appear to be driven by the RBI's exhortations to the banks to provide loan relief to the rural borrowers living in areas affected by droughts. Privately owned banks respond most effectively to a temporary credit demand shock. Overall, we present positive evidence on the role of commercial banks in optimal capital allocation, in contrast to some recent studies that have found their role sub-optimal.

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Table 1A: Summary Statistics (Bank Credit Variables)

The table reports key summary statistics of our banking variables. We report credit outstanding, number of accounts and average account size for direct agricultural credit as well as total bank credit at the district-year level. The data is from annual volumes of the Reserves Bank of India's 'Basic Statistical Returns for Scheduled Commercial Banks' The data covers the period from 1993-94 to 2009-10.

Variables	N	Mean	SD	P25	Median	P75
Credit (in Million INR)						
Direct Agricultural	9152	1673.216	3007.372	222.86	683.2775	1835.815
Total Bank	9152	19402.23	161475.3	1049.257	3160.433	8892.059
Ratio of Direct Agri to Total Bank	9152	0.253	0.187	0.117	0.227	0.365
Number of Accounts						
Direct Agricultural	9152	45721.29	60360.47	12646.5	29194	57458
Total Bank	9152	124225.5	305073.5	35168.5	73128.5	135147.5
Ratio of Direct Agri to Total Bank	9152	0.421	0.179	0.305	0.428	0.541
Average Account Size (INR)						
Direct Agricultural	9151	44130.75	140757	13320.15	24479.22	44326.88
Total Bank	9152	86878.71	133281.4	25050.05	49404.22	95114.48
Ratio of Direct Agri to Total Bank	9151	0.598	1.121	0.377	0.552	0.739

Table 1B: Summary Statistics (Weather Variables)

The table reports key summary statistics of the weather variables we use in our regressions. We obtain the annual Standardized Precipitation Index (SPI) measure for 458 districts from Pai, Sridhar, Guhathakurta and Hatwar (2010). The SPI measure reported is from 1993-2003. We obtain annual rainfall from the National Data Centre of the Indian Meteorological Department. This data is from 1993-2010. Long Period Averages are obtained from IndiaStat. Drought definitions for both SPI and PN-based come from Pai, Sridhar, Guhathakurta and Hatwar (2010).

Variables	N	Mean	SD	P25	Median	P75
SPI-based						
SPI measure	4015	0.039	0.917	-0.5	0.03	0.55
Drought (SPI<-1)	4015	0.110	0.313	0	0	0
PN-based						
Annual Rainfall (mm)	6182	1236.304	838.3516	703.2	1013.95	1490.2
% deviation from LPA	3989	4.498	39.226	-18.134	0.263	19.628
Drought (deviation<-25%)	3989	0.175	0.380	0.000	0.000	0.000

Table 2: Agricultural Credit and Drought

The table reports the regression results of the following equation on our sample covering 436 districts of India from 1993-2010:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

In Panel A, the dependent variable is the logged value of agricultural credit outstanding in district d at the end of fiscal year t. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use three measures of drought - based on the SPI index value, PN rainfall and a third composite measure which is 1 if both the other measures of drought indicate that the district had a drought. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District fixed effects are included in all specifications Results reported in odd-numbered columns come from specifications with year fixed effects while those in even-numbered columns have region-year fixed effects. In Panel B, the dependent variable is the logged ratio of direct agricultural outstanding to total bank credit outstanding. Everything else remains the same.

	Panel A: Log Direct Agricultural Credit						*Panel B: Log (Direct Agricultural Credit/Total Bank Credit)*					
	1	2	3	4	5	6	1	2	3	4	5	6
Drought (SPI)	.050***	.042***					.042***	.039***				
	{.002}	{.003}					{.002}	{.001}				
Drought (PN)			.037**	.029**					.031***	.028**		
			{.014}	{.047}					{.008}	{.017}		
Drought (SPI and PN)					.111**	.079**					.084**	.059*
					{.025}	{.034}					{.036}	{.053}
Log Other Bank Credit	.300***	.261***	.213***	.182***	.259***	.192***	-.543***	-.577***	-.604***	-.627***	-.542***	-.604***
	{.000}	{.000}	{.000}	{.000}	{.001}	{.009}	{.000}	{.000}	{.000}	{.000}	{.000}	{.000}
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Region-Year FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Adj. R-squared	0.953	0.96	0.961	0.965	0.943	0.951	0.938	0.947	0.937	0.943	0.943	0.951
Observations	3267	3267	3308	3308	1394	1394	3249	3249	3328	3328	1386	1386

Standard errors are cluster adjusted at district level.

P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 3: Drought and Credit in Neighboring Districts

The table reports the regression results of the following equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

The dependent variable is the logged value of the average direct agricultural credit outstanding in districts neighboring district d at the end of fiscal year t. By neighboring district, we mean districts which share a physical border with district d. We exclude neighboring districts which had a drought. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1 and 0 otherwise. We use three measures of drought - based on the SPI index value, PN rainfall and a third composite measure which is 1 if both the other measures of drought indicate that the district had a drought. The average of total bank credit excluding direct agricultural credit outstanding in districts neighboring district d at the end of fiscal year t is included as a control for bank and economic development in the district. District fixed effects are included in all specifications. Results reported in odd-numbered columns come from specifications with year fixed effects while those in even-numbered columns have region-year fixed effects.

	Log Direct Agricultural Credit in Neighboring Districts					
	1	2	3	4	5	6
Drought (SPI)	-0.01	-0.008				
	{.595}	{.629}				
Drought (PN)			-.046**	-.049***		
			{.011}	{.007}		
Drought (SPI and PN)					0.062	0.05
					{.162}	{.277}
Log Other Credit in Neighboring Districts	.294***	.280***	.305***	.305***	.327***	.324***
	{.000}	{.000}	{.000}	{.000}	{.000}	{.000}
District FE	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO
Region-Year FE	NO	YES	NO	YES	NO	YES
Adj. R-squared	0.953	0.963	0.953	0.958	0.923	0.932
Observations	3227	3227	3380	3380	1398	1398

Standard errors are cluster adjusted at district level.
P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 4a: Other Credit and Drought

The table reports the regression results of the following equation on our sample covering 436 districts of India from 1993-2010:

$$PersonalLoans_{dt} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

In Panel A, the dependent variable is the logged value of personal loans outstanding in district d at the end of fiscal year t. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use three measures of drought - based on the SPI index value, PN rainfall and a third composite measure which is 1 if both the other measures of drought indicate that the district had a drought. Total bank credit excluding personal loans outstanding in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District and region-year fixed effects are included in all specifications.

In Panel B, the dependent variable is the logged value of non-direct agricultural, non-personal loans outstanding. The control variable is the difference between total bank credit and the value of the dependent variable outstanding. There are no other differences between the specifications in Panel A and Panel B. Panel C has the logged value of total bank credit as the dependent variable. Since total bank credit is now on the left hand side, there is no control variable in Panel C. The fixed effects are the same as in the two other panels.

	Panel A: Log Personal Loans			*Panel B: Log Non-Personal, Non-Agricultural Loans*			*Panel C: Log Total Bank Credit*		
	1	2	3	1	2	3	1	2	3
Drought (SPI)	-0.005			-0.007			0.005		
	{.708}			{.747}			{.799}		
Drought (PN)		-0.002			0.002			0.009	
		{.895}			{.898}			{.556}	
Drought (SPI and PN)			0.017			0.016			.081*
			{.505}			{.719}			{.052}
Log Other Credit	.324***	.324***	.271***	.646***	.671***	.507***			
	{.000}	{.000}	{.000}	{.000}	{.000}	{.000}			
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.978	0.977	0.98	0.963	0.948	0.968	0.96	0.961	0.962
Observations	3264	3344	1392	3263	3343	1391	3274	3363	1397

Standard errors are cluster adjusted at district level. P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 4b: Agricultural Credit and Drought in Rural Districts

The table reports the regression results of the following equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

We run the regression on a sample of those districts where the ratio of direct agricultural credit to total bank credit outstanding is above the national median. In Panel A, the dependent variable is the logged value of direct agricultural credit outstanding in district d at the end of fiscal year t. In Panel B, we use the logged value of personal loans outstanding instead. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use three measures of drought - based on the SPI index value, PN rainfall and a third composite measure which is 1 if both the other measures of drought indicate that the district had a drought. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District and region-year fixed effects are included in all specifications.

	Panel A: Log Direct Agri Credit			*Panel B: Log Personal Loans*		
	1	2	3	1	2	3
Drought (SPI)	.050**			0.011		
	{.012}			{.548}		
Drought (PN)		.030*			0	
		{.070}			{.999}	
Drought (SPI and PN)			.110***			0.049
			{.001}			{.244}
Log Other Credit	.200***	.247***	.274**	.293***	.459***	.341**
	{.005}	{.000}	{.039}	{.000}	{.000}	{.012}
District FE	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.951	0.964	0.944	0.97	0.973	0.969
Observations	1655	1721	679	1655	1754	678

Standard errors are cluster adjusted at district level.

P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 4c: Agricultural Credit and Government Relief Expenditure in Previous Drought

This table reports the regression results of the following equation:

$$AgriCred_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * ReliefExpd_{st-k} + \zeta ReliefExpd_{st-k} + \beta OtherCred_{dt} + \varepsilon_{dt}$$

The dependent variable is the logged value of agricultural credit outstanding in district d at the end of fiscal year t. $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use two measures of drought - based on the SPI index value and on PN rainfall. $ReliefExpd_{st-k}$ is the logged value of real per capita non-plan expenditure on relief on account of natural calamities in state s in the year which coincides with the most recent occurrence of drought in district d. Data on relief expenditure is from the Reserve Bank of India's handbook on state government finances. District fixed effects are included in both specifications. Odd numbered columns have results from including year fixed effects while region-year fixed effects are included in even numbered columns.

	Log Direct Agri Credit			
	1	2	3	4
Drought (SPI)	.085*	0.05		
	{.071}	{.269}		
Drought (SPI) * Previous DY Log (Non-plan relief expenditure per capita)	-0.021	-0.004		
	{.246}	{.811}		
Drought (PN)			-0.018	-0.016
			{.412}	{.422}
Drought (PN) * Previous DY Log (Non-plan relief expenditure per capita)			0.029	0.021
			{.275}	{.404}
Log Other Credit	.359***	.339***	.216***	.210***
	{.000}	{.000}	{.000}	{.000}
Previous Drought Year Log (Non-plan relief expenditure per capita)	-0.011	-0.016	0.074	0.068
	{.750}	{.645}	{.273}	{.268}
District FE	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
Region-Year FE	NO	YES	NO	YES
Adj. R-squared	0.963	0.966	0.973	0.973
Observations	1364	1364	1613	1613

Standard errors are cluster adjusted at district level. P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 5: Drought Prone Districts

Panel A of the table reports the regression results of the following equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} {*} Drought\text{-}Prone_d + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

The dependent variable is the logged value of agricultural credit outstanding in district d at the end of fiscal year t. $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use two measures of drought - based on the SPI index value and PN rainfall. $Drought\text{-}Prone_d$ is 1 for those districts which have been identified as susceptible to frequent droughts. We get the list of 99 drought-prone districts from IndiaStat. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District and region-year fixed effects are included in both specifications.

The tests in Panel B and Panel C are identical to those in Table 2. However, they contain results from tests run on sub-samples of the data. Panel B has results from running the tests for a sample containing drought-prone districts only while Panel C has the results when we run the tests for the sample containing non drought-prone districts.

	Log Direct Agricultural Credit					
	Panel A: Full Sample		*Panel B: Drought- Prone Districts*		*Panel C: Non Drought Prone Districts*	
	1	2	1	2	1	2
Drought (SPI)	.045***		0.019		.044***	
	{.003}		{.620}		{.004}	
Drought (SPI)*Drought Prone	-0.015					
	{.683}					
Drought (PN)		.041**		-0.005		.040**
		{.015}		{.875}		{.018}
Drought (PN)*Drought Prone		-0.053				
		{.135}				
Log Bank Credit	.261***	.183***	0.218	0.162	.266***	.188***
	{.000}	{.000}	{.107}	{.171}	{.000}	{.000}
District FE	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.96	0.965	0.945	0.957	0.962	0.966
Observations	3267	3308	749	681	2518	2627

Standard errors are cluster adjusted at district level. P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 6: Source of Increased Agricultural Credit

The table reports the regression results of the following equation on our sample covering 436 districts of India from 1993-2010:

$$AgriCredit_{dt} = \alpha + \gamma_d + v_t + \delta Drought_{dt-1} + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

In Panel A, the dependent variable is the logged number of direct agricultural accounts in district d at the end of fiscal year t. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use three measures of drought - based on the SPI index value, PN rainfall and a third composite measure which is 1 if both the other measures of drought indicate that the district had a drought. Total number of credit accounts excluding direct agricultural credit accounts in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District fixed effects are included in all specifications. Results reported in odd-numbered columns come from specifications with year fixed effects while those in even-numbered columns have region-year fixed effects.

In Panel B, the dependent variable is the log of the average amount outstanding in a direct agricultural credit account in district d at the end of fiscal year t. We calculate the average amount by dividing the amount outstanding by the number of accounts. Our control variable is the log of the average amount outstanding in non-direct agricultural credit accounts in district d at the end of fiscal year t. Our drought variable as well as fixed effects are the same as in Panel A.

	Panel A: Log Number of Direct Agri Credit Accounts						*Panel B: Log Average Size of Direct Agri Credit Accounts*					
	1	2	3	4	5	6	1	2	3	4	5	6
Drought (SPI)	0.012	0					.030**	.035***				
	{.385}	{.987}					{.021}	{.009}				
Drought (PN)			.024*	0.005					.021*	.025**		
			{.062}	{.656}					{.059}	{.023}		
Drought (SPI and PN)					0.008	-0.019					.111***	.104***
					{.796}	{.518}					{.005}	{.004}
Log Number of Other Accounts	.652***	.536***	.486***	.469***	.720***	.638***						
	{.000}	{.000}	{.000}	{.000}	{.000}	{.000}						
Log Average Size of Other Accounts							.205***	.183***	.183***	.171***	.200***	.159***
							{.000}	{.000}	{.000}	{.000}	{.001}	{.000}
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Region-Year FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Adj. R-squared	0.957	0.969	0.937	0.945	0.948	0.957	0.927	0.935	0.953	0.958	0.94	0.949
Observations	3259	3259	3280	3280	1389	1389	3193	3193	3315	3315	1370	1370

Standard errors are cluster adjusted at district level.

P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 7: Drought and Agricultural Credit by Type of Bank

The table reports the regression results of the following equation:

$$AgriCredit_{dtb} = \alpha + \gamma_d + \nu_t + \delta Drought_{dt-1} + \beta OtherCredit_{dtb} + \varepsilon_{dt}$$

The dependent variable is the logged value of direct agricultural credit outstanding in district d at the end of fiscal year t for banks belonging to bank ownership group b. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use only the PN measure of drought in this case since our data starts in 2000. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t for banks belonging to bank ownership group b is included as a control for bank and economic development in the district. District and region-year fixed effects are included in all specifications. Panel A deals with all banks, Panel B with just public sector banks, Panel C with Regional Rural Banks and Panel D with private sector banks including foreign banks.

	Log Direct Agricultural Credit			
	Panel A: All Banks	*Panel B: Public Sector Banks*	*Panel C: Regional Rural Banks*	*Panel D: Private Sector Banks*
	1	2	4	6
Drought (PN)	0.016	0.016	-0.009	.178*
	{.237}	{.275}	{.730}	{.086}
Log Other Credit	.137***	.128***	.820***	.206***
	{.000}	{.000}	{.000}	{.003}
District FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Adj. R-squared	0.974	0.969	0.94	0.85
Observations	2349	2341	2016	1732

Standard errors are cluster adjusted at district level.
P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 8a: Agricultural Credit, Drought and Elections

Panel A of the table reports the regression results of the following equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * Election_{st} + \zeta Election_{st} + \beta OtherCred_{dt} + \varepsilon_{dt}$$

The dependent variable is the logged value of agricultural credit outstanding in district d at the end of fiscal year t. $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use two measures of drought - based on the SPI index value and PN rainfall. $Election_{st}$ is coded 1 when the state saw an assembly election between October of year t-1 and September of year t. Data on election dates is from the Election Commission of India. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District and region-year fixed effects are included in both specifications.

The tests in Panel B and Panel C are identical to those in Table 2. However, they contain results from tests run on sub-samples of the data. The sub-sample used in Panel B has data from election years only, while the sub-sample used in Panel C only has non-election years.

Log Direct Agricultural Credit

	Panel A: Whole Sample		*Panel B: Election Years*		*Panel C: Non Election Years*	
	1	2	3	4	5	6
Drought (SPI)	.038**		0.107		.047***	
	{.014}		{.255}		{.006}	
Drought (SPI)*Election Year	0.031					
	{.390}					
Drought (PN)		0.022		0.053		0.028
		{.168}		{.305}		{.126}
Drought (PN)*Election Year		0.029				
		{.299}				
Election Year	-0.01	-0.012				
	{.334}	{.276}				
Log Bank Credit	.255***	.183***	.374***	.174***	.297***	.227***
	{.000}	{.000}	{.002}	{.009}	{.000}	{.000}
District FE	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.958	0.965	0.94	0.956	0.951	0.961
Observations	3250	3308	662	733	2588	2575

Standard errors are cluster adjusted at district level. P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 8b: Agricultural Credit, Drought and Elections (by Type of Bank)

The table reports the regression results of the following equation:

$$AgriCredit_{dtb} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * Election_{st} + \zeta Election_{st} + \beta OtherCred_{dtb} + \varepsilon_{dt}$$

The dependent variable is the logged value of direct agricultural credit outstanding in district d at the end of fiscal year t for banks belonging to bank ownership group b. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use only the PN measure of drought in this case since our data starts in 2000. $Election_{st}$ is coded 1 when the state saw an assembly election between October of year t-1 and September of year t. Data on election dates is from the Election Commission of India. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t for bank group b is included as a control for bank and economic development in the district. District and region-year fixed effects are included in all specifications. Panel A deals with all banks, Panel B with just public sector banks, Panel C with Regional Rural Banks and Panel D with private sector banks including foreign banks.

	Log Direct Agricultural Credit			
	Panel A: All Banks	*Panel B: Public Sector Banks*	*Panel C: Regional Rural Banks*	*Panel D: Private Sector Banks*
	1	2	3	4
Drought (PN)	0.01	0.004	0.009	0.178
	{.498}	{.801}	{.756}	{.128}
Drought (PN)*Election Year	0.033	.057*	-0.063	0.007
	{.246}	{.087}	{.307}	{.968}
Election Year	.138***	.129***	.823***	.207***
	{.000}	{.000}	{.000}	{.003}
Log Bank Credit	-.025**	-.030**	-.051*	-0.047
	{.042}	{.032}	{.056}	{.500}
District FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Adj. R-squared	0.974	0.969	0.94	0.85
Observations	2349	2341	2016	1732

Standard errors are cluster adjusted at district level.
P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 9a: Agricultural Credit and Government Relief Expenditure

This table reports the regression results of the following equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * ReliefExpd_{st} + \beta OtherCred_{dt} + \varepsilon_{dt}$$

The dependent variable is the logged value of agricultural credit outstanding in district d at the end of fiscal year t. $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use three measures of drought - based on the SPI index value, PN rainfall and a measure which signals drought only when the other two measures both signal drought. $ReliefExpd_{st}$ is the logged value of real per capita non-plan expenditure on relief on account of natural calamities. Data on relief expenditure is from the Reserve Bank of India's handbook on state government finances. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t is included as a control for bank and economic development in the district. District and year fixed effects are included in both specifications. Region-year fixed effects are included in even numbered columns.

	Log Direct Agri Credit					
	1	2	3	4	5	6
Drought (SPI)	0.074	0.069				
	{.150}	{.162}				
Drought (SPI) * Log (Non-plan relief expenditure per capita)	-0.01	-0.01				
	{.630}	{.614}				
Drought (PN)			0.004	0.019		
			{.940}	{.717}		
Drought (PN) * Log (Non-plan relief expenditure per capita)			0.011	0.003		
			{.469}	{.855}		
Drought (PN and SPI)					0.024	0.094
					{.868}	{.569}
Drought (PN and SPI) * Log (Non-plan relief expenditure per capita)					0.033	0.001
					{.582}	{.988}
Log Other Credit	.300***	.259***	.213***	.205***	.258***	.216**
	{.000}	{.000}	{.000}	{.000}	{.001}	{.010}
District FE	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO
Region-Year FE	NO	YES	NO	YES	NO	YES
Adj. R-squared	0.95	0.957	0.961	0.962	0.943	0.948
Observations	3235	3235	3259	3259	1394	1394

Standard errors are cluster adjusted at district level.

P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 9b: Agricultural Credit and Government Relief Expenditure (by Type of Bank)

This table reports the regression results of the following equation:

$$AgriCredit_{dtb} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1}*ReliefExpd_{st} + \beta OtherCred_{dtb} + \varepsilon_{dt}$$

The dependent variable is the logged value of direct agricultural credit outstanding in district d at the end of fiscal year t for banks belonging to bank ownership group b. The independent variable of interest $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use only the PN measure of drought in this case since our data starts in 2000. $ReliefExpd_{st}$ is the logged value of real per capita non-plan expenditure on relief on account of natural calamities. Data on relief expenditure is from the Reserve Bank of India's handbook on state government finances. Total bank credit excluding direct agricultural credit outstanding in district d at the end of fiscal year t for bank group b is included as a control for bank and economic development in the district. District and region-year fixed effects are included in all specifications. Panel A deals with all banks, Panel B with just public sector banks, Panel C with Regional Rural Banks and Panel D with private sector banks including foreign banks.

	Log Direct Agricultural Credit			
	Panel A: All Banks	*Panel B: Public Sector Banks*	*Panel C: Regional Rural Banks*	*Panel D: Private Sector Banks*
	1	2	3	4
Drought (PN)	0.066	0.064	0.043	-0.141
	{.190}	{.234}	{.698}	{.757}
Drought (PN)* Log (Non-plan relief expenditure per capita)	-0.016	-0.015	-0.017	0.105
	{.280}	{.342}	{.623}	{.448}
Log Other Credit	.153***	.149***	.810***	.227***
	{.000}	{.000}	{.000}	{.001}
District FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Adj. R-squared	0.972	0.967	0.94	0.839
Observations	2300	2291	1984	1688

Standard errors are cluster adjusted at district level.
P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Table 10: Agricultural Credit and Drought: Before and After 1998

The Table below reports the regression results of the following equation:

$$AgriCredit_{dt} = \alpha + \gamma_d + \nu_t + \delta_1 Drought_{dt-1} + \delta_2 Drought_{dt-1} * D_{1998} + \beta OtherCredit_{dt} + \varepsilon_{dt}$$

In Panel A, the dependent variable is the logged value of agricultural credit outstanding in district d at the end of fiscal year t. In Panel B, we use the logged value of personal loans outstanding in district d at the end of fiscal year t as the dependent variable. $Drought_{dt-1}$ has value 1 if district d had a drought in calendar year t-1. We use three measures of drought - based on the SPI index value, PN rainfall and a third composite measure which is 1 if both the other measures of drought indicate that the district had a drought. D_{1998} is an indicator variable which takes the value 1 for all observations which are after 1998, and 0 otherwise. The control variable is the difference between total bank credit and the value of the dependent variable outstanding. District and region-year fixed effects are included in all specifications.

	Log Direct Agricultural Credit			*Log Personal Loans*		
	1	2	3	4	5	6
Drought (SPI)	.050***			-0.024		
	{.010}			{.212}		
Drought (SPI)*Post 98	-0.016			0.039		
	{.587}			{.143}		
Drought (PN)		0.02			-0.018	
		{.701}			{.665}	
Drought (PN)*Post 98		0.01			0.019	
		{.854}			{.686}	
Drought (SPI and PN)			.134*			-0.044
			{.096}			{.480}
Drought (SPI and PN)*Post 98			-0.076			0.085
			{.386}			{.189}
Log Bank Credit	.261***	.182***	.193***	.324***	.324***	.270***
	{.000}	{.000}	{.009}	{.000}	{.000}	{.000}
District FE	YES	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.96	0.965	0.951	0.978	0.977	0.98
Observations	3267	3308	1394	3264	3344	1392

Standard errors are cluster adjusted at district level.
P-values are reported in brackets. Level of Significance: * 0.10, ** 0.05, *** 0.01

Figure 1: Drought Frequency

The figure plots the percentage of districts in India that suffer from drought during every year in our sample period (1993-2009). The series for drought measured by SPI runs from 1993 to 2003 while for drought measured by PN rainfall it covers the entire period.

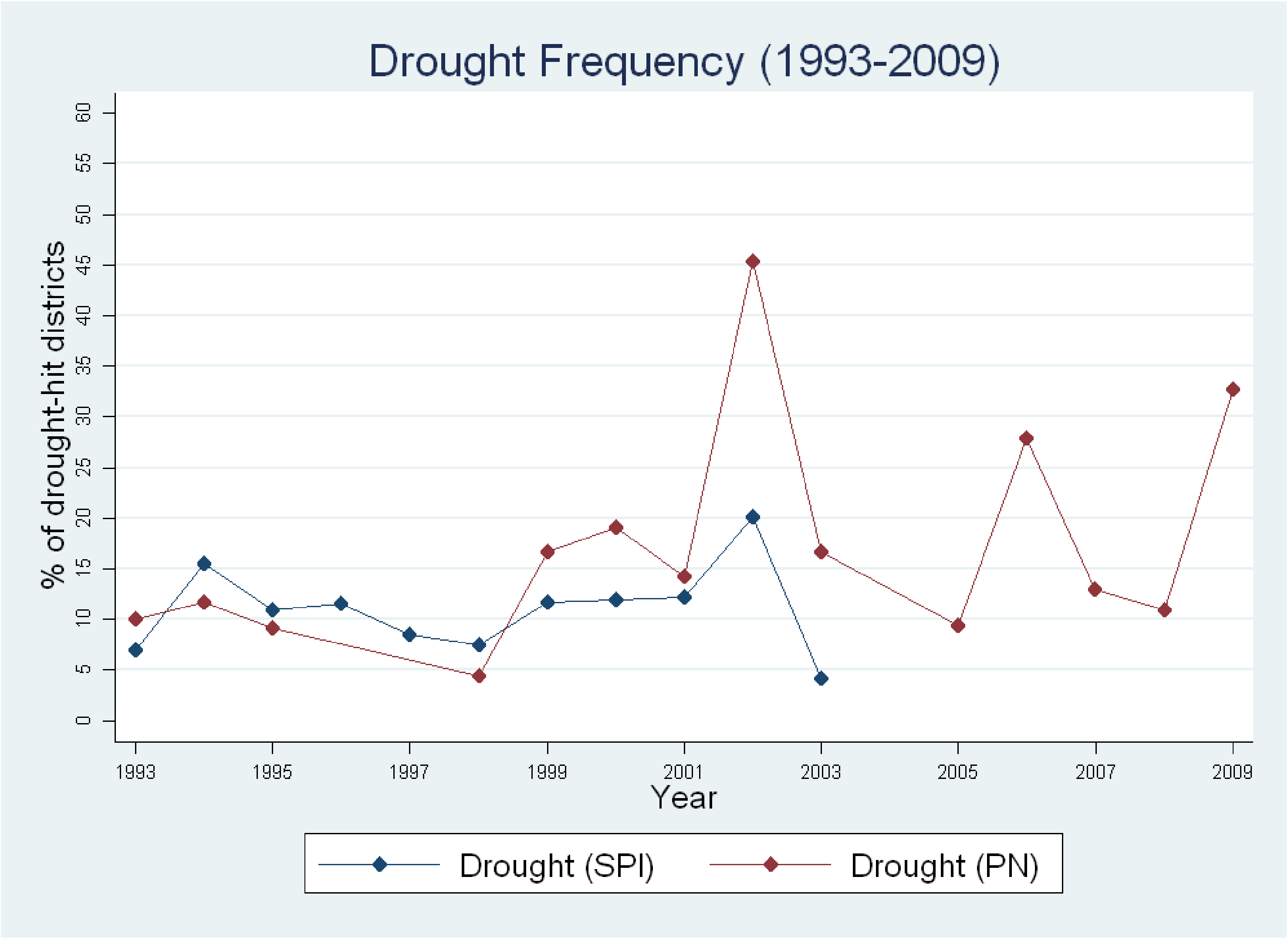


Figure 2: Drought Prone Districts

The figure plots the distribution of drought prone districts in India. Drought prone districts are identified from the Compendium of Environment Statistics, 2002

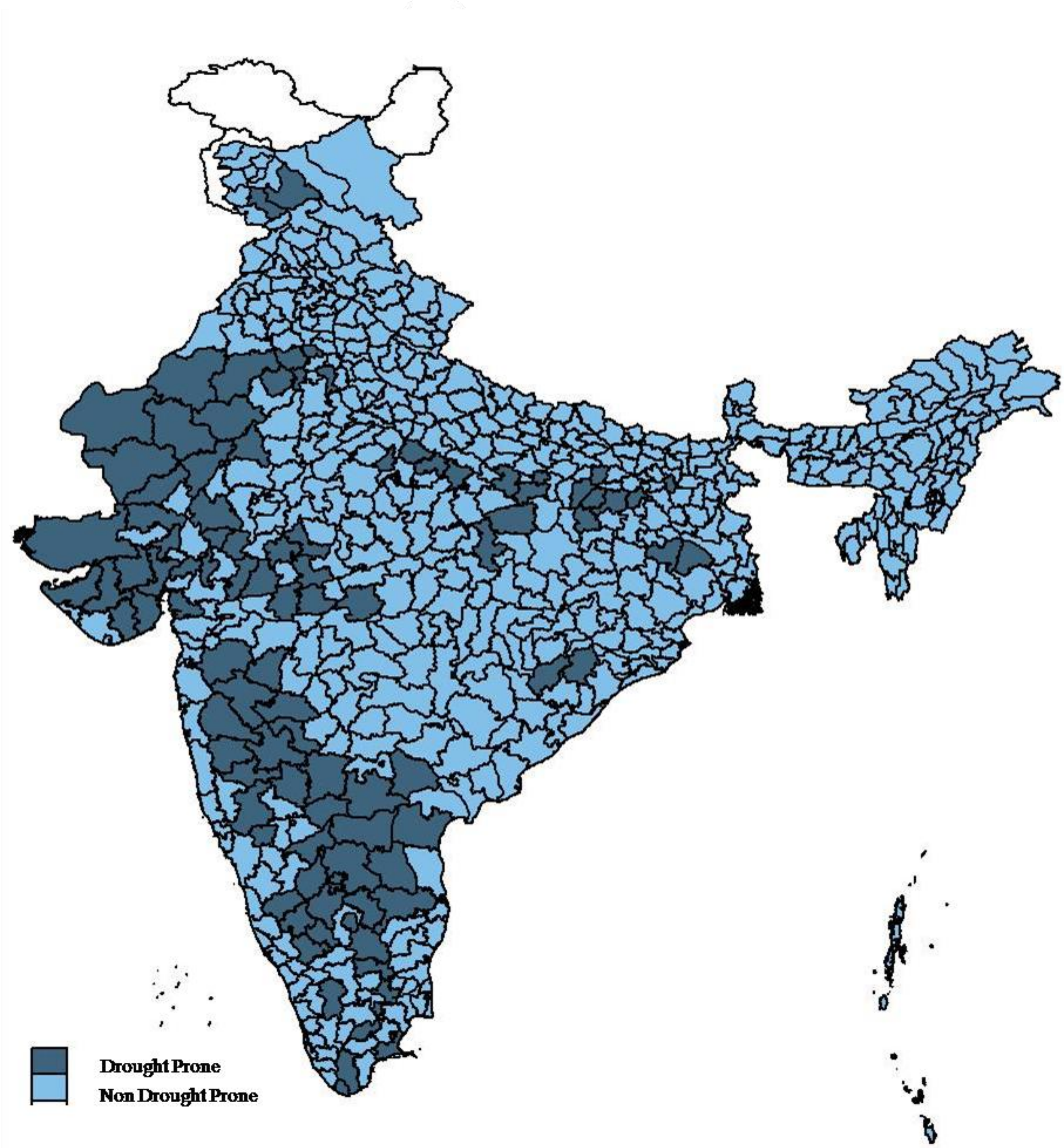


Figure 3: Dynamics of Drought Effect on Agricultural Credit

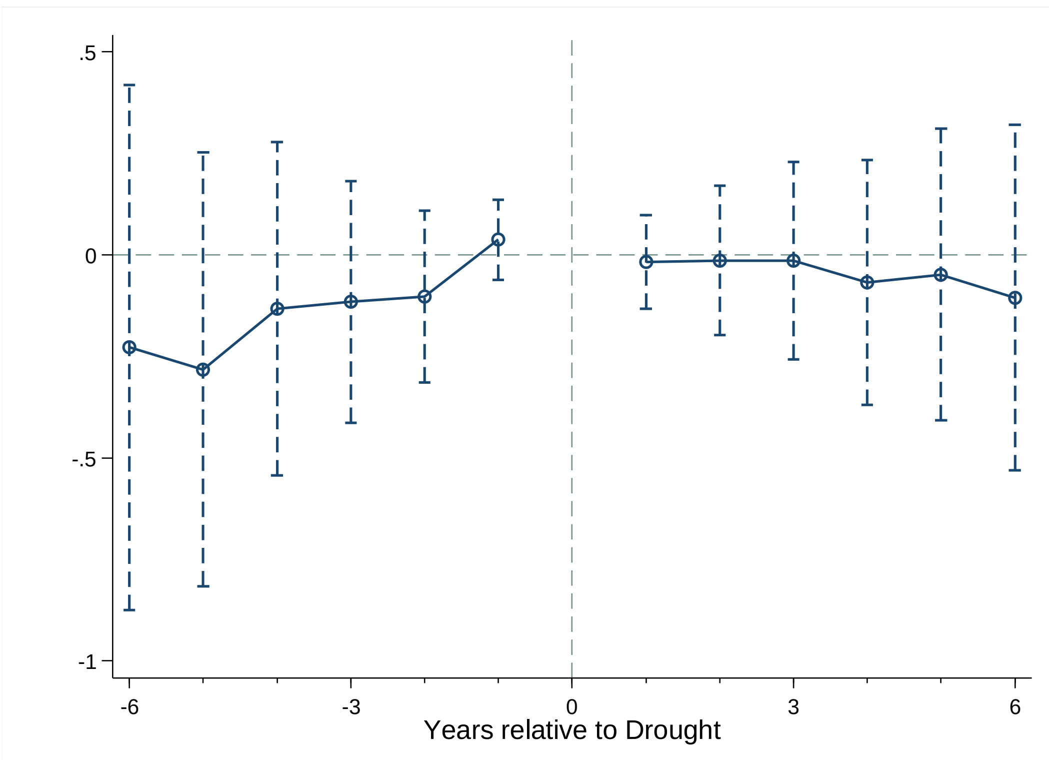
The figure plots the dynamics of agricultural credit outstanding in the years preceding and following a drought. We consider a window from 6 years prior to 6 years after a drought for only those districts which have had just one drought within our sample period.

We report the coefficients estimated from the following regression:

$$AgriCredit_{dt} = \alpha + \gamma_d + v_t + \delta_1 D_{dt-1}^{-6} + \delta_2 D_{dt-1}^{-5} + \ldots + \delta_{11} D_{dt-1}^{5} + \delta_{12} D_{dt-1}^{6} + \beta BankCredit_{dt} + \varepsilon_{dt}$$

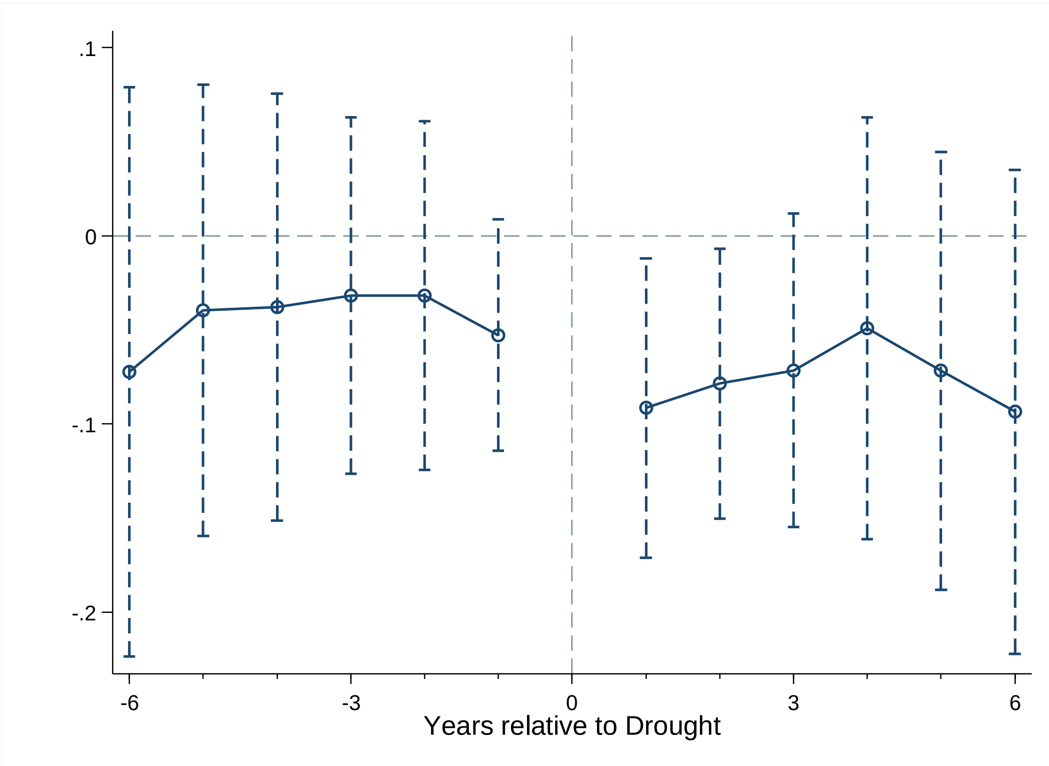
D^{-i} equals 1 for districts in the ith year before a drought and 0 otherwise, while D^{i} equals 1 for districts in the ith year after a drought and 0 otherwise. Since we exclude the dummy for the year of the drought, we are able to estimate the dynamics relative to the year of the drought. We include district fixed effects, year fixed effects and district-year fixed effects as well as the log of bank credit as a control. Our dependent variable is the log of agricultural credit outstanding.

The circles represent the point estimates of the respective dummy coefficient while the dashed lines represent 90% confidence intervals, adjusted for district-level clustering. In (a), we report results where the drought measure is SPI-based. There are 42 districts with the time period being from 1993-2003. In (b), the drought measure is based on PN rainfall. It covers 61 districts over 1993-2009.



(a) Drought measured using SPI

Figure 3: Dynamics of Drought Effect on Agricultural Credit (contd.)



(b) Drought measured using PN rainfall