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Does access to external finance improve productivity? Evidence from a natural experiment[☆]

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ABSTRACT

We study the relation between access to finance and productivity. Our contribution to the literature is a clean identification of a causal effect of access to finance on productivity. Specifically, we exploit an exogenous shift in demand for a product to expose how producers adapt their productivity in the presence of varying levels of access to finance. We use a triple differences testing approach and find that production increases the most over the sample period in areas with relatively strong access to finance, even in comparison with a control group. This result is statistically significant and robust to a variety of controls, alternative variables, and tests. The causal effect of access to finance on productivity that we find speaks to the larger role of finance in economic growth.

1. Introduction

Does finance cause economic growth? The literature addressing the question of whether finance creates growth (e.g., Hicks, 1969) or follows growth (e.g., Robinson, 1952) is vast, and dates back at least as far as Schumpeter (1912). Because finance and growth are endogenously determined, one of the biggest hurdles facing empirical work in this area is clean identification of the direction of causality. Little exists in the way of clearly exogenous variation in finance for researchers to exploit. Further, what the precise channels are through which any finance-to-growth effect operates remain unclear. This paper examines the impact of access to finance on productivity as a candidate explanation to help bridge the gap, and we use a natural experiment created by a government mandate to achieve identification in our tests.

In the United States, the Energy Policy Act of 2005 mandated that renewable fuel additives in gasoline nearly double to 7.5 billion gallons by 2012. This act, combined with rising crude oil prices at the time and federal biofuel tax credits, created an exogenous shift in demand for US corn, the main ingredient in US ethanol production. We use these events as a natural experiment to examine the finance-growth nexus: whether access to finance is a critical component for encouraging economic growth and productivity. We use county-level data on crops, weather, and finance in midwestern states (the primary corn-producing region in the United States known colloquially as the "corn belt") during 2000–2006 to study the

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productivity response of farmers to the shift in demand for corn that the Energy Policy Act of 2005 created.

Consistent with the view that finance affects growth, we find a large shift in corn productivity in response to the ethanol-induced shift in demand and that this productivity improvement is most pronounced in counties with high levels of bank deposits. We use a triple differences (differences-in-differences-in-differences, DIDID) testing procedure. The first difference is the response of productivity to greater versus lesser access to external finance. The second difference is the response of productivity to a shift in demand. The third difference is the response of productivity for the commodity with increased demand (corn) versus a control crop that had no shift in demand (soybeans). Our main variable of interest is the interaction of these three: productivity response for corn (relative to soybeans) during the ethanol boom (relative to the pre-ethanol mandate period) across varying levels of access to finance.

To construct our tests, we need an appropriate measure of productivity for the farming industry. Farmers and economists (e.g., Feder, 1985, among many others) commonly view crop yields as a relevant measure of farming productivity. Crop yield is output per unit of land, specifically, the harvested number of bushels of a crop per acre planted in that crop. These data are available for each crop by county on an annual basis. The advantages of our proxy for productivity compared with, say, total factor productivity are that it is easily measured, need not be estimated like a total factor productivity measure, and is specific to the industry we study.

We also need an appropriate empirical measure of access to finance. In similar spirit to Becker (2007), we use a measure based on aggregate county-level bank deposits. Becker (2007) shows that local bank deposit supply has a positive and significant effect on local economic outcomes through the loans that the banks make. What is particularly useful for our study is Becker's result that the market for bank capital is segmented geographically. That is, at the metropolitan statistical area (MSA) and zip code levels, local deposits (and hence loan supply) affect local economic outcomes. Becker's result is consonant with Petersen and Rajan (2002), who find that the median distance between small businesses and their banks in recent years is only about five miles. For comparison, the size of the median county in our sample is 416 square miles, or about 20 miles by 20 miles. Given the highly localized nature of bank lending, our access to finance measure is, arguably, a good one. Nonetheless, we examine a number of alternative measures of access to finance and find similar results.

The magnitude of our results suggests that the effect of access to finance on growth is economically nontrivial. A simple two-way sort demonstrates that, in response to the shift in demand for corn, corn yields in the midwestern United States have increased by 10.4 bushels per acre more in counties with high bank deposits than in counties with low bank deposits over the sample period in comparison with the control crop. To provide some perspective, the standard deviation of corn yields across counties in Iowa, the state producing the most corn, was only 8.8 bushels per acre in 2006.

Our DIDID procedure allows us to dismiss many alternative hypotheses. Our results indicate that the increase in productivity is restricted to corn, which experienced a large demand shift, but not our control crop (soybeans); productivity is greater during the ethanol boom period compared with before the ethanol boom period; the increase in productivity occurs in areas (counties) that have substantial access to finance, but not those that have less financial development. Thus, a competing alternative hypothesis must relate to corn only, to the ethanol boom period only, and to the finance-heavy counties only. This rules out, among other things, general trends in farm productivity. There are other determinants of crop yields besides access to finance. Soil fertility and weather are two obvious things that affect agriculture. We control directly for weather with precipitation and temperature variables and control indirectly for soil fertility and other unobservables with state or county fixed effects.

One potential concern is that of reverse causality. If a county experiences high crop yields, this leads to more wealth for the farmers in the county, who could then deposit their wealth in local banks. In this case, finance and productivity are linked, but finance follows (not facilitates) productivity. We use additional tests to help rule out this alternative explanation. First, we use the number of bank branches in a given county as an alternative measure of access to finance. Although in the long run bank branches could migrate to where there is economic prosperity, in the short run the number of bank branches should be insensitive to changes in crop yields, yet be indicative of greater access to finance. Second, we use an instrumental variables approach with either lagged measures of access to finance or demographic variables serving as instruments for current access to finance. This instrumental variables approach forces the exogenous portion of access to finance to explain productivity. These alternative approaches leave all of our main conclusions unchanged.

Our results are robust to a variety of additional changes in our baseline tests including changes in our measure of access to finance, our control crop, our productivity benchmark, our event defining the natural experiment (the sudden switch from sugar to high fructose corn syrup by major soft drink manufacturers in 1985, which we use in conjunction with a different measure of access to finance based on bank branching deregulation (as in Jayaratne and Strahan, 1996), general trends in farm productivity, and unobservable time invariant factors such as stable demographic characteristics that would be absorbed by state or county fixed effects specifications.

Our paper connects the literature on determinants of economic growth with that on how corporate financing constraints affect investment decisions. The financial constraints literature shows that the financing frictions and the costs of external finance can have substantial impacts on firms' operating decisions such as investment timing and allocations in real assets (Whited, 1992, 2006; Chava and Roberts, 2008). And, like Bakke and Whited (2008), we examine how financing frictions affect real economic outcomes. While their paper looks at corporate

Table 1
Crop details. This table specifies the variety of each crop we study in the paper. This table also contains information quantifying recent US harvests of each crop measured and the time of year that each crop is planted and harvested. Harvest amounts, as well as planting and harvest seasons information, come from the United States Department of Agriculture.

Crop	Variety	2002 harvested acres (millions)	2007 harvested acres (millions)	Planting season	Harvest season
Corn	Yellow-kernelled (field corn)	68.2	85.4	Spring	Fall
Soybeans	Yellow	72.4	63.3	Late spring	Fall

operating decisions, such as employment and investment, we examine the ultimate outcomes, in the form of changes in productivity, of operating decisions.

Finance and growth papers similar to ours include Gatti and Love (2006), who study the relation between access to credit and total factor productivity in a sample of Bulgarian firms. Our findings and theirs are consistent, but one of the important differences is that we study a developed economy, which sets our paper apart from the vast majority of papers in the finance and growth literature (for example, Djankov and Hoekman, 1999; Maurel, 2001). We also employ a testing procedure that resolves the problem of endogeneity between access to finance and productivity, and we use an unambiguous measure of productivity, instead of estimated measures such as total factor productivity.

The rest of the paper is organized as follows. Section 2 has institutional details to provide background information on the research setting. Section 3 describes the analytic framework from which we approach the relation between access to finance and productivity. Section 4 discusses our data and describes their basic properties. Section 5 describes our methods for testing the relation between access to finance and productivity, and it gives results. Section 6 discusses robustness tests for these results, and Section 7 concludes.

2. Institutional detail

This section contains institutional details on corn and soybeans crops, ownership of American farms, and ethanol production.

2.1. Corn and soybeans

Corn, soybeans, and other crops are bought and sold on midwestern US agricultural spot markets. According to the 2002 Census of Agriculture conducted by the National Agricultural Statistics Service (NASS), a division of the United States Department of Agriculture (USDA), corn and soybeans are the two largest planted cash crops in the United States, with harvests of 68.2 million acres and 72.4 million acres, respectively. Table 1 contains basic information regarding these crops. In recent years, soybeans were the largest harvested crop in the United States. By 2007, however, corn supplanted soybeans as the largest harvested cash crop in the United States. Despite the change of status between corn and soybeans as the most widely harvested crop, they remain the two largest harvested crops, overall.

Corn comes in two main varieties: sweet corn and yellow-kernelled corn (i.e., field corn). Yellow-kernelled corn is an actively traded commodity; sweet corn is not. Yellow-kernelled corn is the main ingredient in ethanol production in the United States, and thus it is the focus of this paper. Soybeans effectively come in only one variety: yellow soybeans.

2.2. Ownership of American farms

A statistical brief published by the Bureau of the Census states: "People own most farmland. Some 2.6 million owners are individuals or families, and they own more than two-thirds of all farm acreage. Fewer than 32,500 non-family-held corporations own farmland, and they own less than 5 percent of all U.S. farmland."[1] Securities and Exchange Commission filings by large American food processing companies (e.g., ConAgra and Archer Daniels Midland) bear this out. Rather than being actively involved in growing crops, these companies are downstream from the actual farming operations, and use harvested crops as inputs to their operations.

2.3. Institutional detail: ethanol

According to a 2007 report from the Economic Research Service, a division of the USDA, the demand for ethanol in the United States has surged due to a number of complementary forces.[2] First, market conditions for crude oil have changed. Crude oil prices averaged $20 per barrel in the 1990s but rapidly grew to a record $59 per barrel in 2006. As crude oil becomes more expensive, ethanol becomes more attractive as an alternative fuel source. Second, the Energy Policy Act of 2005 mandated that renewable fuel additives in gasoline (ethanol is a principal renewable fuel) reach 7.5 billion gallons by 2012. Further, this new legislation provides no liability protection for the gasoline additive methyl tertiary butyl ether (MTBE). Many states have recently banned MTBE, a suspected carcinogen that can contaminate aquifers of drinking water. Without liability protection, ethanol becomes an increasingly attractive substitute. Third, new tax laws provide further incentives for biofuels. Tax credits of 51 cents per gallon of ethanol blended with gasoline are available to US gasoline manufacturers under the current federal tax law. Imported ethanol faces a tariff

[1] Source: http://www.census.gov/apsd/www/statbrief/sb93_10.pdf.
[2] Source: Paul C. Wescott, Economic Research Service (http://www.ers.usda.gov/Publications/FDS/2007/05May/FDS07D01/fds07D01.pdf).

of 54 cents per gallon (with the exception of duty-free status for certain Central American and Caribbean countries on up to 7% of the US market for imported ethanol). Hahn (2008) discusses economic and political issues affecting ethanol production. The ethanol production industry in the midwestern US is not heavily concentrated. Our snapshot of ethanol production capacity data for 2006 includes information for 120 ethanol plants in the midwestern United States. Sixty-seven of those plants are owned by limited liability corporations (LLCs) or limited partnerships (LPs), suggesting that small companies own a large percentage of the plants. Most of the remaining plants are owned by corporations, although we cannot determine the size of many of the corporations because they are not publicly traded. As of April 2006, the 67 plants owned by LLCs or LPs have a combined ethanol production capacity of 3,713 million gallons of ethanol per year. The remaining plants have a combined production capacity of 4,737 million gallons of ethanol per year.

3. Hypothesis development

Our analysis focuses on how a producer's budget at time *t* is a function of her ability to borrow against future cash flows and the present value of her future production. A producer's budget increases with her ability to borrow against future cash flows, and a producer can enhance her productivity by taking advantage of this expanded budget. In our empirical tests, we capture cross-sectional variation in ability to borrow against future cash flows with county-level bank deposits. The relation between budget and bank deposits follows because, when bank deposits are high, the banks holding them will have more funds to provide as loans (i.e., access to finance increases), as in Becker (2007). A producer's budget further increases with the present value of future production. This effect follows because lenders favorably view expected increases in production. That is, a producer is able to borrow greater amounts when the value of her future productivity is expected to be high.

Our empirical tests center on the idea that the ethanol boom increased the present value of future cash flows to growing corn and that the ability to borrow against these future cash flows varies cross-sectionally county by county depending on the accessibility of finance. Although the available data are too coarse to allow us to scrutinize individual farms' specific uses of an expanded budget—that is, we do not know if corn farmers use their larger budgets for increased capital expenditures, for labor costs, or for buying more land—we can test the idea that the availability of external finance could allow producers in an area to improve their productivity in response to a shift in demand for their product.

4. Data

Our data are on an annual frequency and are made up of county-level variables from the 12 states of the midwestern United States (Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin) from 2000 to 2006. According to our calculations from USDA data, these 12 states account for about 88% of all US corn production.

4.1. Independent variables

The first independent variable of interest is the ethanol boom period dummy. We select 2005 as the starting year of the ethanol boom. The ethanol boom period dummy is equal to one in 2005 and 2006 and zero in previous years. If farmers correctly anticipated the enactment of the Energy Policy Act of 2005, then such foresight would bias against finding our results.

The second independent variable of interest is access to finance. In similar spirit to Becker (2007), we use county-level bank deposits to proxy for access to finance. Bank deposits data come from the Federal Deposit Insurance Corporation (FDIC) website (http://www2.fdic.gov/sod/index.asp). We sum all bank deposits held by banks within a given county insured by the FDIC each year. Noting that many banks rely heavily on deposit financing, Becker (2007) shows a positive effect of local deposit supply on loan supply, and hence local economic activity. We expect better access to finance in counties with high levels of bank deposits.

We also expect banks with more deposits to make more loans. This appears to be the case in our sample. Because we are interested particularly in agricultural loans, we compute the correlation between deposits and loans to finance agricultural production from 2000 to 2006. The data we use are bank-level loan and deposit data from the Reports of Condition and Income (Call Reports) published by the FDIC. The correlations between deposits and loans to finance agricultural production are positive and statistically significant. For all banks in the United States the correlation is 0.52; for the subsample of unit banks in the midwestern United States the correlation is 0.65. We are particularly interested in unit banks because they tend to be small and local, and farmers tend to borrow from them.[3] The bottom line is that banks with more deposits make more agricultural loans, which is a key insight for understanding the channel through which local bank deposits affect local farming outcomes.

Our baseline measure of access to finance is a poor-finance county dummy variable (*Low Deposits*) equal to one if the level of bank deposits in a given county falls into the bottom quintile of all county-level bank deposits for a given year and zero otherwise.

Although other sources of external finance are available to farmers (e.g., federal farm loans programs), commercial banks provide the majority of non-real estate farm loans (Cramer, Jensen, and Southgate, 2001, and our own calculations from USDA data). The presence of other sources of finance works against our findings by making local bank finance less important to local economic outcomes. Fig. 1 shows the change of relative densities of bank deposits across the midwestern United States from 2000 to 2006.

[3] Koo, Duncan, and Taylor (1998) find that local commercial bank financing is the greatest source of credit used by farmers in the United States. Specifically, 63% of farmers use local commercial bank financing. Only 4% of farmers use nonlocal commercial bank financing.

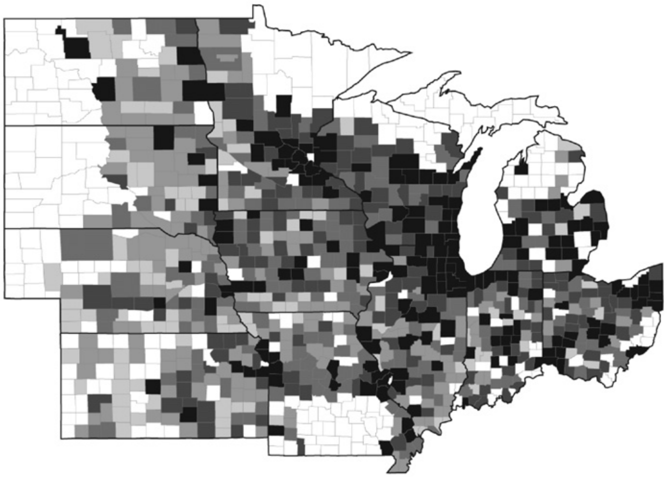

Fig. 1. Changes of county-level bank deposits. This figure shows the change of relative density of bank deposits within counties in the midwestern United States from 2000 to 2006. Darker shading indicates greater growth in bank deposits.

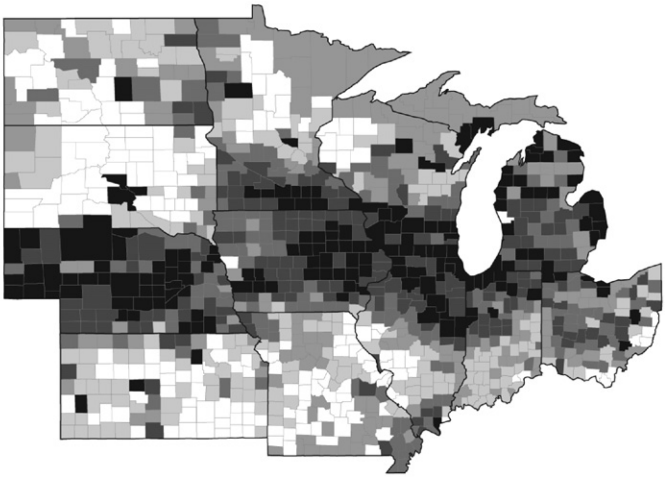

Fig. 2. Changes of county-level corn yields. This figure shows the change of relative density of corn yields produced by counties in the midwestern United States from 2000 to 2006. Darker shading indicates relatively greater growth in corn yields.

4.2. Dependent variables

Our primary dependent variable is crop yield, measured in bushels per acre, which proxies for productivity. Bushel sizes vary somewhat by crop, but they are typically around 50 harvested pounds of a given crop. Crop yields data come from the NASS. Figs. 2 and 3 show the changes of concentrations of corn and soybeans yields across the midwestern United States from 2000 to 2006.

4.3. Control variables

We collect county-level ethanol production capacity as of April 2006, measured in millions of gallons produced per year. Ethanol production capacity data come from the Renewable Fuels Association (RFA) website (www.ethanolrfa.org/industry/locations/). We have two measures of ethanol production capacity: ethanol production capacity in place, and ethanol production capacity under construction or planned for expansion.

Fig. 4 shows a map of ethanol production capacity as of 2006 plotted over county-level changes in corn yields. We sum at the county level across ethanol plants in the county to determine the ethanol production capacity in place and under construction or planned for expansion. A total of 110 counties in our sample have ethanol production capacity in place, under construction, or planned for expansion as of 2006. Ethanol producers could choose to build their plants in counties with high corn yields in an effort to minimize transportation costs. Therefore, we expect to see a positive relation between yields and whether or not a county has an ethanol production facility.

Not surprisingly, temperature and precipitation play an important role in the production of corn and soybeans

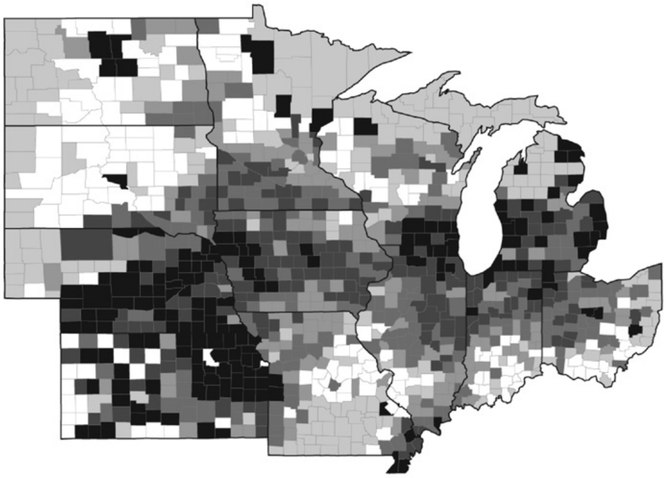

Fig. 3. Changes of county-level soybean yields. This figure shows the change of relative density of soybean yields produced by counties in the midwestern United States from 2000 to 2006. Darker shading indicates relatively greater growth in soybean yields.

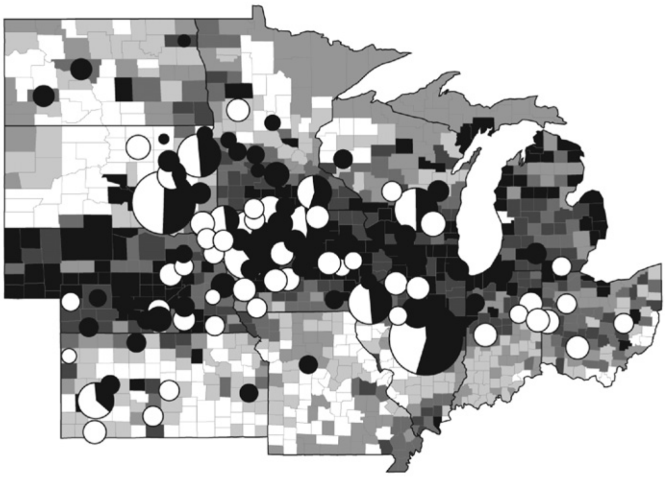

Fig. 4. Ethanol production capacity plotted over changes of corn yields. County-level ethanol production capacity data are represented by pie charts. Black slices represent in-place ethanol production capacity as of April 2006, and white slices represent ethanol production capacity planned for expansion. Pie size represents current plus future ethanol production capacity. Layered underneath the ethanol production capacity data are relative densities of changes of corn yields produced by counties in the midwestern United States from 2000 to 2006. Darker shading indicates relatively greater growth in corn yields.

(see Thompson, 1986; Carlson, Todey, and Taylor, 1996). We control for meteorological conditions in our multivariate regressions by including growing degree days and inches of precipitation (and, as a robustness test, their squared terms to allow for nonlinearities). We collect daily observations for both of these variables from Weather Underground (www.weatherunderground.com), a web-based commercial weather service. We consider the growing seasons listed in Table 1 and sum both of these variables from May 1 through October 31 for each year. Growing degree days (GDD) is a typical measure of temperature relevant for agriculture and is defined as

$$GDD = \sum_{d=1}^{D} \max\left\{\frac{T_{max,d}+T_{min,d}}{2} - T_{base}, 0\right\}, \quad (1)$$

where D equals the total number of days from May 1 through October 31, $T_{max,d}$ equals the maximum temperature for a given day, measured in degrees Fahrenheit, $T_{min,d}$ equals the minimum temperature for a given day, measured in degrees Fahrenheit, and T_{base} equals the base temperature of 50 degrees Fahrenheit.

Weather stations are distributed sporadically across counties in the midwestern United States. Some counties have one or more weather stations, but most have none. We pick four weather stations for each state that are approximately evenly distributed geographically, and we assign the data from the weather stations to the closest counties. This approach assumes that meteorological conditions within regional clusters of counties do not have significant variation. This is probably a safe

Table 2

Summary statistics. Panel A presents pooled summary statistics for county-year-crop observations. We examine counties in the 12 midwestern states each year from 2000 to 2006 with nonzero yields of corn and soybeans. Individual crop yields are measured in bushels per acre. Crop yields data come from the National Agricultural Statistics Service, which is affiliated with the United States Department of Agriculture. *Deposits* represents the sum of all deposits held within banks insured by the Federal Deposit Insurance Corporation (FDIC) for a given county and a given year, measured in millions of dollars. *Branches* represents a count of all bank branches insured by the FDIC for a given county and a given year. Deposits and branches data come from the FDIC's website. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. Population, unemployment, and per capita income data come from the US Census Bureau's website. *Precipitation* and *GDD* represent the inches of precipitation and number of growing degree days in an associated crop's region from May through October of a given year, respectively. Meteorological data come from weatherunderground.com. Panel B presents summary statistics for standard deviations of crop yields at the county level. For example, *N* is the number of counties growing a particular crop any year from 2000 to 2006, Mean is the average standard deviation of counties' crop yields from 2000 to 2006, and so forth.

Variable	*N*	Mean	Standard Deviation	Minimum	25%	Median	75%	Maximum
Panel A								
Corn Yield	6,723	130.2	34.5	0	109.3	135.4	155.1	220.0
Soybeans Yield	6,323	38.9	10.1	2.9	32.0	40.0	46.9	67.0
Deposits	13,594	1,064	5,677	0.8	151	300	638	180,338
Branches	13,594	23.6	57.5	0	7	11	21	1,616
Pop. Density	12,918	261.3	1,242.7	0.9	29.0	72.2	175.1	32,789.8
Unemployment	13,594	4.8	1.6	1.8	3.6	4.6	5.7	13.1
Per Capita Income	13,594	26.2	4.6	8.9	23.1	25.7	28.6	52.5
Precipitation	12,975	25.0	21.5	2.5	16.1	20.7	27.3	227.5
GDD	12,975	2,836	587	1,267	2,434	2,833	3,219	4,289
Panel B								
SD of Counties' Corn Yields	982	19.8	7.3	0	15.0	18.5	23.8	46.6
SD of Counties' Soybean Yields	929	6.5	2.1	0	5.2	6.4	7.8	14.6

assumption because the midwestern states exhibit little variation in topography and geology, especially within each state.[4]

We control for population density, because it could be related to deposits (urban areas are likely to have more financial institutions). Population density could also directly correlate with crop yields. For example, counties with higher levels of urbanization could be less suitable for agricultural growth (due to poorer air quality or less arable land) or because, when population density increases, residents urbanize land less suitable for agriculture, increasing yields per planted acre. We use the US Census Bureau (http://www.census.gov/main/www/access.html) estimates of county populations each year from 2000 to 2006 and calculate population density by dividing the estimate of a county's population for a given year by the county's square mileage. Local economic conditions could be correlated with crop yields. We control for local economic conditions with two additional variables: county-level unemployment rates and county-level per capita income. Data on unemployment and per capita income are available from the US Census Bureau (http://www.census.gov/support/DataDownload.htm). Both of these measures are available on an annual basis from 2000 to 2006. We also control for whether a county had an ethanol plant in place in 2006 or had an ethanol plant under construction or planned for expansion. Ethanol production capacity and access to finance could be correlated.

The county-level data for corn and soybeans in the midwestern United States from 2000 to 2006 give 12,849 county-year-crop observations. Table 2 provides summary statistics for our independent, dependent, and control variables. Panel A presents pooled summary statistics for county-year-crop observations. The maximum values for deposits and population density come from Cook County, Illinois, which contains the city of Chicago. Panel B presents summary statistics for standard deviations of county-level crop yields. This information is useful for interpreting the economic magnitudes of the forthcoming regression results. We present correlations among key variables in Table 3.

5. Methods and results

This section describes our baseline econometric methods and the main results of the paper.

5.1. Agricultural lending in the corn-heavy counties

We motivate our baseline tests by comparing agricultural lending in the top corn-producing counties in the midwestern United States with agricultural lending in the rest of the country. The idea here is to determine whether the share of agricultural loans in total loans has increased in counties experiencing the greatest growth in corn yields.

We begin by calculating the change in average corn yield in all midwestern counties from 2000 to 2006. We rank these changes and focus on the one hundred counties exhibiting the greatest gains in corn yields over this time period. We randomly select one unit bank for each of these one hundred counties, and calculate the bank's ratio of its loans to finance agricultural production to total loans, which we call simply an agriculture loan ratio, for

[4] For a whimsical piece of evidence supporting this claim, see Fonstad, Pugnatch, and Vogt (2003).

Table 3
Correlation matrix. This table presents pairwise correlations of county-year observations. We examine all counties in the 12 midwestern states each year from 2000 to 2006 and report information on corn and soybeans. Individual crop yields are measured in bushels per acre. Crop yields data come from the National Agricultural Statistics Service, which is affiliated with the United States Department of Agriculture. *Deposits* represents the sum of all deposits held within banks insured by the Federal Deposit Insurance Corporation (FDIC) for a given county and a given year, measured in thousands of dollars. *Branches* represents a count of all bank branches insured by the FDIC for a given county and a given year. Deposits and branches data come from the FDIC's website. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. Population, unemployment, and per capita income data come from the US Census Bureau's website. *GDD* and *Precipitation* represent the number of growing degree days, and inches of precipitation in an associated crop's region from May through October of a given year, respectively. Meteorological data come from weatherunderground.com. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	GDD	Corn Yield	Soybeans Yield	Deposits	Branches	Population Density	Unemployment	Per Capita Income
Corn Yield	0.028**							
Soybeans Yield	0.062***	0.779***						
Deposits	−0.014	0.021*	−0.007					
Branches	−0.017	0.042***	0.004	0.941***				
Population Density	0.106***	−0.069***	−0.012	0.012	0.008			
Unemployment	−0.014	−0.037***	−0.077***	0.044***	0.008***	0.046***		
Per Capita Income	−0.130***	0.187***	0.162***	0.271***	0.386***	0.290***	−0.228***	
Precipitation	0.097***	0.082***	0.101***	−0.021*	−0.016	0.009	−0.021**	−0.026***

the first and last years of the sample period (2000 and 2006). We then match our randomly selected unit bank with a matching unit bank outside the midwestern United States. For the year 2000, we classify all unit banks outside the midwestern United States into ten bins based on total assets (bank size) and then subdivide each of the ten bins into ten additional bins by total loans to finance agricultural production (agricultural specialization of the bank). Therefore, we have one hundred bins. We determine which of the one hundred bins each of the unit banks from our top-one hundred-corn-growth counties would be in and then choose as the best match in that bin the unit bank that minimizes the sum of squared percentage differences in total assets and total loans to finance agricultural production.

We compare the sample and matched banks' agriculture loan ratio from 2000 to 2006. We find that this ratio declines by 0.014 for the non-midwestern matched banks from 2000 to 2006 (perhaps due to an increase in real estate lending). However, the agriculture loan ratio increases by 0.013 for unit banks residing in the top-one hundred-corn-growth counties. Both the increase in agriculture loan ratio for our midwestern banks and the decrease in the same for the non-midwestern matched banks are statistically significant at the 5% level. Table 4 displays these results. For the sake of comparison, the average standard deviation of the ratio of the agriculture loan ratio for all banks in the United States from 2000 to 2006 was 0.011, so these differences are economically meaningful as well.

Table 4
Univariate tests of agricultural lending as a fraction of total loans. This table presents the mean ratio of loans to finance agricultural production to total loans from 2000 to 2006. We compute this ratio for one hundred unit banks in the midwestern United States residing in counties experiencing the greatest growth in corn yields over our sample period and matching banks outside the midwestern United States with similar levels of agricultural loans and total assets as of 2000. We use ** to represent significance at the 5% level based on two-tailed *t*-tests.

Year	Top-one hundred-corn-growth counties	Matched counties outside the midwest
2000 mean	0.174	0.221
2006 mean	0.187	0.207
Difference	0.013**	−0.014**

5.2. Differences-in-differences-in-differences: two-way sorts

We sort crop yields into 35 groups. First, we split the sample by year into seven groups (i.e., the data for each year from 2000 to 2006 become a group). Within each year, we then form five quintiles based on the county-level bank deposits. That is, we place yields coming from counties with the lowest quintile of bank deposits in the first group, yields coming from counties with the next-lowest quintile of bank deposits in the second group, and so forth, until we finish by placing yields coming from counties with the highest quintile of bank deposits in the fifth and final group. Then we average the yields. This procedure creates a seven-by-five matrix of average yields.

We calculate the first difference by subtracting the average yield of the low bank deposits group of a given year from the average yield of the high bank deposits group for the same year. We perform a two-tailed *t*-test to determine if the difference is statistically significant. We perform this procedure for each year, from 2000 through 2006. The first difference demonstrates whether, for a given year, the average yield from a county with relatively high access to finance is higher than the average yield from a county with relatively low access to finance.

We calculate the second difference by subtracting the first difference for 2000 from the first difference for 2006. We perform a two-tailed t-test to determine if the second difference is statistically significant. This second difference demonstrates whether the gap in productivity between counties with high access to finance and low access to finance is simultaneously expanding with the increased demand for corn.

We calculate the third difference after repeating this entire process for a control crop (soybeans). By comparing the second difference of corn with that of soybeans, we produce a third difference. This third difference allows us to assess whether the increasing gap found by the second difference is unique to corn or simply a by-product of an economy-wide boom in agricultural productivity.

Table 5 gives results for the DIDID approach. Our results show that corn yields in the midwestern United States have increased by 10.4 bushels per acre more in counties with high bank deposits than in counties with low bank deposits over the sample period. To put this in perspective, 10.4 bushels per acre is approximately half of a standard deviation of an average county's annual corn yield per acre. In contrast, the difference in soybean yields between counties with varying levels of bank deposits shows no significant change over the sample period.

These results demonstrate how access to finance can affect productivity when an exogenous increase in demand for a product arises. Corn producers in counties with high levels of bank deposits respond to the exogenous shift in demand for corn by ramping up productivity. However, corn producers in counties with low levels of bank deposits do not increase productivity to the same extent. The demand for soybeans has not experienced a similar exogenous shift. Therefore, as expected, the difference in soybean productivity across counties with low and high levels of bank deposits has remained stable. We show this result graphically in Fig. 5.

Table 5 shows an interesting feature of the relation between finance and productivity. The largest inter-quintile increase in productivity comes between the lowest and second-lowest quintiles. The difference in the mean corn yield between the lowest and second-lowest quintile is 11.9 bushels, which is almost double the difference between second-lowest and the middle quintile. Differences between other quintiles are even smaller.

We interpret this result as evidence that access to finance has a nonlinear influence on productivity. That is, increases in access to finance improve productivity, but decreasingly so. Accordingly, we use a dummy variable (equal to one for county-year observations in the bottom quintile of bank deposits and zero otherwise) for low access to finance in our regressions that follow. We also use other measures, such as a continuous measure of deposits and number of bank branches, and find similar results.

5.3. Regression specification: differences-in-differences

We perform multivariate ordinary least squares (OLS) regressions. Eq. (2) shows our basic regression approach. Subscripts i, t, and k denote county, year, and crop, respectively.

$$\begin{aligned}\text{Yield}_{i,t,k} = {} & \beta_1 \text{ Corn Dummy}_k \cdot \text{Access to Finance}_{i,t} \cdot \text{Ethanol Period}_t \\ & +\beta_2 \text{ Corn Dummy}_k \cdot \text{Access to Finance}_{i,t} \\ & +\beta_3 \text{ Corn Dummy}_k \cdot \text{Ethanol Period}_t \\ & +\beta_4 \text{ Corn Dummy}_k \\ & +\beta_5 \text{ Access to Finance}_{i,t} \cdot \text{Ethanol Period}_t \\ & +\beta_6 \text{ Access to Finance}_{i,t} \\ & +\beta_7 \text{ Ethanol Period}_t + \text{Controls} + \text{Constant} + \varepsilon_{i,t,k} \qquad (2)\end{aligned}$$

Ethanol Period is a dummy variable equal to one during the ethanol boom period (2005 and after) and zero otherwise. This variable proxies for the demand for corn, because the ethanol boom period provides an impetus for corn farmers to boost productivity. We do not include year dummy variables to capture time varying trends in corn farming productivity because doing so would introduce collinearity with *Ethanol Period*. Instead, we

Table 5

Univariate tests of corn and soybean yields using a two-way sort. Each year-deposit quintile bin contains the average corn (top) and soybean (bottom) yield for year and deposit quintiles. Crop yields data come from the National Agricultural Statistics Service's (NASS) website, which is affiliated with the United States Department of Agriculture (USDA). *Difference* represents the difference between the average yields associated with the highest and lowest levels of deposits for a given year (right column), or the difference between the average yields associated with the earliest and latest years for a given deposit quintile (bottom row). We use two-tailed t-tests to examine the differences in means. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Year	Deposits: low to high					Difference (high–low)
2000	114.6	128.6	135.9	138.5	134.3	19.7***
	32.8	36.5	40.2	39.7	39.1	6.2***
2001	117.0	127.3	134.2	133.7	130.4	13.4***
	36.0	38.6	40.1	40.2	39.0	3.0***
2002	105.6	117.0	122.0	121.1	115.2	9.6***
	32.9	37.2	38.9	39.0	38.0	5.1***
2003	114.5	122.8	130.5	137.4	138.0	23.5***
	32.3	30.9	32.8	33.8	32.2	−0.1
2004	134.0	148.0	154.4	155.9	151.0	17.0***
	37.0	40.8	43.4	44.0	42.6	5.6***
2005	125.2	136.9	140.2	142.8	140.8	15.6***
	40.2	42.7	44.2	43.9	43.7	3.5***
2006	117.2	130.5	140.4	146.5	147.3	30.1***
	39.0	41.1	43.8	45.1	44.9	5.9***
Mean	118.3	130.2	136.8	139.4	136.7	
	35.7	38.3	40.5	40.8	39.9	
Difference (2006–2000)	2.6	1.9	4.5**	8.0***	13.0***	10.4***
	6.2***	4.6***	3.6***	5.4***	5.8***	−0.3

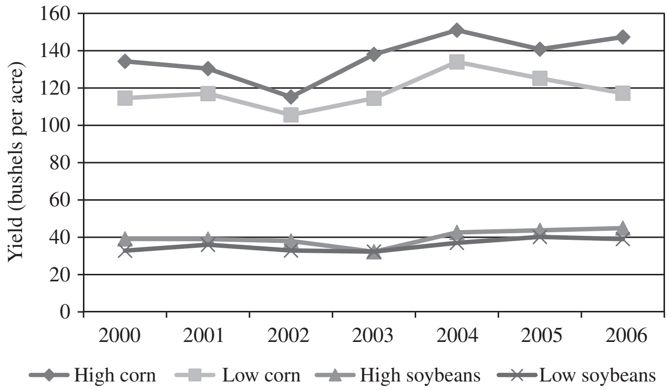

Fig. 5. Average corn and soybean yields in high and low bank deposit quintiles. This figure contains time series plots of four variables measured annually from 2000 to 2006: the average corn yield in counties with bank deposits in the highest quintile, the average corn yield in counties with bank deposits in the lowest quintile, the average soybean yield in counties with bank deposits in the highest quintile, and the average soybean yield in counties with bank deposits in the lowest quintile.

control for time varying mean effects with our agricultural control (soybeans). We also use other measures to control for systemic time variation in productivity.

The first OLS regression pools all of the county-year-crop observations. The dependent variable is crop yield. We separately winsorize corn and soybean yields at 1% and 99% to mitigate the effects of outliers, though this procedure does not materially affect any of our results or conclusions. We regress yields on bank deposits, the ethanol boom period dummy variable, and dummy variables for each crop.

We also include a number of interaction terms in the regression. We interact crop dummies with the low-quintile deposits dummy variable and the ethanol boom period dummy variable. We expect this term to be negative and significant for corn, but insignificant for soybeans. We expect a negative relation for corn because corn yields should be lowest in counties with low access to finance (the low-quintile deposits dummy variable equals one), yet particularly so when the demand for corn is high (the ethanol boom period dummy variable equals one) due to increasing interest in ethanol. We expect insignificant coefficients for soybeans because this crop has not experienced an exogenous shift in demand. We include interaction terms for crop dummy variables with the low-quintile deposits dummy variable and for crop dummy variables with the ethanol boom period dummy. For control variables, we include the natural logarithm of population density, the unemployment rate, per capita income, the natural logarithm of inches of precipitation, and the natural logarithm of growing degree days. (If we do not take logged values of these control variables, our main results are all qualitatively unchanged.) To the extent that warmer weather and more rainfall are good for crop yields, we expect positive relations between both growing degree days and crop yields and also between precipitation and crop yields. The relations between weather and crop yields could be nonlinear or non-monotonic or both—e.g., warm weather or precipitation could be beneficial to growing conditions only to a point—so we also run tests with squared terms for our weather variables for robustness purposes. We do not tabulate results that include these higher-ordered terms, but our main results do not change if we include them.

5.4. *Difference-in-differences regression results for corn and for soybeans*

Our main results appear in Tables 6 and 7. In Table 6 we regress separately corn yields, and then soybeans yields, on the following variables: the low-quintile deposits dummy variable; the ethanol period dummy variable; our population, economic, and weather controls; and, our variable of primary interest, the interaction between the low-quintile deposits dummy variable and the ethanol period dummy variable, which captures whether productivity responded least in counties with low access to finance after the shift in demand for corn created by the ethanol boom. We expect the coefficient on this interaction term to be negative and statistically significant for corn.

We perform three separate regressions. The first regression includes no geographical dummy variables, while the second and third regressions include either state or county fixed effects. When we exclude geographical dummy variables, identification comes from both cross-sectional and time series variation. Including state dummy variables removes any unobserved heterogeneity at the state level and forces identification of the regression coefficients through cross-sectional differences at the county level or time series variation within a state or county or both. Including county fixed effects forces identification of the regression coefficients solely through time series variation within a county. In this last specification, time invariant factors such as soil fertility and highly persistent demographic characteristics such as the intelligence and religiosity of the county's farmers cannot drive our results. Standard errors are robust to heteroskedasticity, and we cluster them at the county level.

Table 6

Individual regressions for corn and soybeans. This table presents ordinary least squares regression results based on county-year-crop observations. The regression specification is $Yield_{i,t}=\beta_1$ *Low Deposits*$_{i,t}\cdot$ *Ethanol Period*$_t+\beta_2$ *Low Deposits*$_{i,t}+\beta_3$ *Ethanol Period*$_t$+*Controls*+*Constant*$+\varepsilon_{i,t}$. The dependent variable is crop yield, measured in bushels per acre. We separately winsorize corn and soybean yields at 1% and 99%. Panel A uses corn yield as the dependent variable, and Panel B uses soybeans yield as the dependent variable. Regression 1 includes no geographical fixed effects; Regression 2 includes state dummy variables; Regression 3 includes county fixed effects. *Low Deposits* is a dummy variable equal to one if the level of bank deposits in a given county falls into the bottom quintile of all county-level bank deposits for a given year, and zero otherwise. *Ethanol Period* is an indicator variable equal to one if the yield is harvested during the ethanol boom period (2005 and 2006) and zero otherwise. *Ethanol County* is a dummy variable equal to one if a given county has an ethanol production facility as of 2006 or has plans to build or expand ethanol production capacity as of 2006. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. *Precipitation* and *GDD* represent the inches of precipitation and number of growing degree days in an associated crop's region from May through October of a given year, respectively. The standard errors are in parentheses. They are robust to heteroskedasticity, and we cluster them at the county level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Independent variables	(1)	(2)	(3)
Panel A: Determinants of corn yields			
Low Deposits · Ethanol Period	−4.196**	−5.812***	−8.320***
	(1.639)	(1.542)	(1.582)
Low Deposits	−6.790**	−0.329	4.679**
	(2.792)	(2.220)	(2.214)
Ethanol Period	6.207***	4.304***	−1.196
	(0.960)	(0.856)	(1.322)
Ethanol County	13.527***	9.482***	–
	(2.497)	(2.065)	(–)
Ln Population Density	4.282***	−1.163	33.914***
	(0.848)	(0.831)	(12.406)
Unemployment	−2.190***	−1.804***	0.059
	(0.469)	(0.421)	(0.486)
Per Capita Income	0.002	0.001***	0.004***
	(0.002)	(0.000)	(0.000)
Ln Precipitation	8.041***	2.762***	8.645***
	(1.271)	(0.995)	(0.715)
Ln GDD	6.878*	1.539	−17.574***
	(3.920)	(3.711)	(3.554)
Constant	34.526	90.266***	0.680
	(31.935)	(28.861)	(63.108)
N	6,608	6,608	6,608
Adjusted R^2	0.125	0.365	0.681
State dummies?	No	Yes	No
County fixed effects?	No	No	Yes
Panel B: Determinants of soybeans yields			
Low Deposits · Ethanol Period	−0.536	−0.902*	−1.620***
	(0.544)	(0.508)	(0.475)
Low Deposits	−1.181	0.114	2.109**
	(0.800)	(0.592)	(0.817)
Ethanol Period	5.365***	4.358***	3.691***
	(0.283)	(0.243)	(0.328)
Ethanol County	3.586***	2.516***	–
	(0.670)	(0.501)	(–)
Ln Population Density	1.432***	−0.701***	3.889
	(0.240)	(0.208)	(4.136)
Unemployment	−1.137***	−1.164***	−0.919***
	(0.135)	(0.117)	(0.131)
Per Capita Income	0.008	0.022***	0.053***
	(0.006)	(0.006)	(0.009)
Ln Precipitation	2.584***	1.065***	3.401***
	(0.331)	(0.271)	(0.216)
Ln *GDD*	2.473**	4.443***	3.395***
	(1.258)	(1.037)	(0.886)
Constant	10.976	1.544	−26.286***
	(9.703)	(7.918)	(20.194)
N	6,241	6,241	6,241
Adjusted R^2	0.149	0.419	0.622
State dummies?	No	Yes	No
County fixed effects?	No	No	Yes

Table 6 gives results for 6,608 county-year corn yield observations and 6,241 county-year soybean yield observations. The regressions reveal a negative and significant relation between crop yields for both corn and soybeans and the interaction between the low-quintile deposits dummy variable and the ethanol boom period. The magnitude of the deposits-ethanol effect on corn productivity is roughly four to six times larger than it is on soybean productivity, depending upon the regression specification. For example, in the first corn yield regression, the coefficient on the interaction between low-quintile deposits and ethanol is −4.2. This result means that, in response to the ethanol-induced demand shock for corn, counties with good access to finance were able to increase productivity by about four bushels of corn per acre more than corn-growing counties with poor access to finance. The analogous effect in soybean production is a 0.5 bushel differential response to the ethanol boom for counties with relatively good access to finance compared with those with poor access to finance. A visual inspection of these two magnitudes suggests that the effect on corn is much larger.

In our specification with county fixed effects, both corn and soybeans productivity show a statistically significant effect of access to finance in response to the ethanol period, though the magnitude is much larger for corn. Our interpretation of this finding is that some economies of scope could exist for soybean production that come from improvements to corn production. For instance, using good access to finance to borrow money to purchase a large piece of farm equipment could have spillover effects to several crops if the equipment is not too specialized.

5.5. Pooled regression results: triple differences

To test formally whether the deposits-ethanol effect is stronger for corn than for soybeans, we pool the corn and soybeans data together and allow the intercepts and slope coefficients for *Low Deposits*, *Ethanol Period*, and the *Low Deposits* · *Ethanol Period* interaction to vary by crop. Our interest is in whether the slope coefficient on *Low Deposits* · *Ethanol Period* is significantly different for corn and soybeans. We test this by examining whether the triple interaction of the corn crop dummy with the low-quintile deposits dummy variable and the ethanol boom period dummy (i.e., *Corn* · *Low Deposits* · *Ethanol Period*) is significantly different from zero. We include our population and weather controls, as well as state dummy variables, county fixed effects, or neither state dummy variables nor county fixed effects. Standard errors are robust to heteroskedasticity, and we cluster them at the county level.

Table 7 gives results for pooled OLS regressions involving 12,849 county-year-crop observations. The regressions reveal a negative and significant relation between crop yields and the triple interaction term of the corn dummy variable, the low-quintile deposits dummy variable, and the ethanol boom period. Consider the first regression. The coefficient on the triple interaction term is −2.7, which means the change in corn yields, net of change in soybean yields, from before to during the ethanol boom is significantly lower in counties with the lowest levels of bank deposits. We interpret this result as follows. Although farmers in all counties might want to increase their productivity in response to the shift in demand for corn, those farmers in counties with little access to finance are less able to respond because they are relatively restricted in their ability to finance a plan for growth.

This result is not being driven by unobserved state- or county-level factors (e.g., a favorable business climate in the state or soil fertility), because the result holds with state fixed effects (Regression 2) and with county fixed effects (Regression 3). Furthermore, the magnitude of the

Table 7

Pooled regressions for corn and soybeans. This table presents pooled ordinary least squares regression results based on county-year-crop observations. The regressions specification is $Yield_{i,t,k}=\beta_1 Corn_k\ Access\ to\ Finance_{i,t}\ Ethanol\ Period_t+\beta_2\ Corn_k\ Access\ to\ Finance_{i,t}+\beta_3\ Corn_k\ Ethanol\ Period_t+\beta_4\ Corn_k+\beta_5\ Access\ to\ Finance_{i,t}\ Ethanol\ Period_t+\beta_6\ Access\ to\ Finance_{i,t}+\beta_7\ Ethanol\ Period_t+Controls+Constant+\varepsilon_{i,t,k}$. The dependent variable is crop yield, measured in bushels per acre. We separately winsorize corn and soybean yields at 1%. We employ three different measures of *Finance* in this table. Regressions 1, 2, and 3 use the following measure of access to finance: a dummy variable equal to one if the level of bank deposits in a given county falls into the bottom quintile of all county-level bank deposits for a given year and zero otherwise. Regression 1 has no geographic fixed effects; Regression 2 includes state dummy variables; Regression 3 includes county fixed effects. Regression 4 measures finance with the standardized log of the sum of all deposits held within banks insured by the Federal Deposit Insurance Corporation (FDIC) for a given county and a given year, in thousands of dollars. Regression 5 measures finance by the standardized log number of bank branches insured by the FDIC for a given county and a given year. *Corn* is a dummy variable equal to one if the given yield is that of a corn crop and zero if the yield is that of a soybean crop. *Ethanol Period* is an indicator variable equal to one if the yield is harvested during the ethanol boom period and zero otherwise. We define the ethanol boom period as 2005 and later. *Ethanol County* is a dummy variable equal to one if a given county has an ethanol production facility as of 2006 or has plans to build or expand ethanol production capacity as of 2006. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. *Precipitation* and *GDD* represent the inches of precipitation and number of growing degree days in an associated crop's region from May through October of a given year, respectively. The standard errors are in parentheses. They are robust to heteroskedasticity, and we cluster them at the county level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Finance is measured by				
	Low deposits dummy			Ln(Deposits)	Ln(Number of bank branches)
Independent variables	(1)	(2)	(3)	(4)	(5)
Corn · Finance · Ethanol Period	−2.723*	−3.003**	−2.898*	0.688	1.056**
	(1.414)	(1.401)	(1.490)	(0.520)	(0.509)
Corn · Finance	−14.031***	−13.846***	−12.766***	4.528***	3.739***
	(1.950)	(1.914)	(1.920)	(0.712)	(0.703)
Corn · Ethanol Period	2.061***	2.054***	1.869***	1.120**	1.385***
	(0.485)	(0.481)	(0.497)	(0.475)	(0.468)
Corn	94.591***	94.728***	95.540***	92.989***	92.931***
	(0.682)	(0.673)	(0.671)	(0.659)	(0.667)
Finance · Ethanol Period	−1.065*	−1.897***	−3.659***	1.449***	1.288***
	(0.544)	(0.561)	(0.758)	(0.296)	(0.291)
Finance	3.121**	7.081***	10.242***	−9.926***	−4.484*
	(1.268)	(1.214)	(1.791)	(2.279)	(2.569)
Ethanol Period	4.688***	3.229***	0.285	−0.133	−0.383
	(0.519)	(0.442)	(0.725)	(0.703)	(0.696)
Ethanol County	8.701***	6.097***	–	–	–
	(1.547)	(1.281)	(–)	(–)	(–)
Ln Population Density	2.941***	−0.860*	20.065***	26.697***	20.982***
	(0.538)	(0.514)	(7.548)	(8.181)	(8.006)
Unemployment	−1.689***	−1.506***	−0.419	−0.305	−0.428
	(0.298)	(0.267)	(0.285)	(0.283)	(0.285)
Per Capita Income	0.001	0.007***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln Precipitation	5.539***	2.180***	6.197***	6.256***	6.194***
	(0.792)	(0.632)	(0.429)	(0.431)	(0.430)
Ln GDD	5.078**	3.101	−7.874***	−7.632***	−8.014***
	(2.563)	(2.374)	(2.099)	(2.098)	(2.093)
Constant	−29.027	−3.968	−62.373	−93.070**	−62.448
	(20.729)	(18.362)	(38.347)	(41.709)	(40.456)
N	12,849	12,849	12,849	12,849	12,849
Adjusted R^2	0.787	0.832	0.890	0.889	0.889
State dummies?	No	Yes	No	No	No
County fixed effects?	No	No	Yes	Yes	Yes

effect is about the same for each of our geographical fixed effects specifications.

To put the magnitude of this result in perspective, consider the second regression, which includes state dummy variables. The coefficient on the triple interaction term is about -3.0 bushels per acre, which is greater than 10% of a standard deviation of an average county's annual corn yield per acre.

As an alternative measure of access to finance, in Regression 4 we substitute for our low-quintile bank deposits dummy variable the natural logarithm of the sum of all deposits held within banks for a given county and a given year. This is a continuous, not discrete, measure. We expect this variable to have a positive relation with productivity. Productivity could be high (low) in areas with high (low) access to finance. The triple interaction term involving the corn dummy variable, bank deposits, and the ethanol boom period dummy is positive but not statistically significant. This result is consistent with our discussion of the nonlinear relation between bank deposits and productivity. Our interpretation of this result is that, in a highly developed economy such as the United States, the marginal impact of access to finance on productivity is greatest where the level of access to finance is lowest. The continuous measure of access to finance, which forces a linear relation upon the data, does not adequately capture this aspect of the relation between access to finance and productivity response to a demand shock.

6. Robustness

This section describes additional tests and results which establish the robustness of our main results.

6.1. Bank branches as an alternative measure of access to finance

A potential criticism of the baseline regressions is that county-level bank deposits could be endogenous with crop yields due to economic prosperity. That is, if a county experiences high crop yields, this leads to more wealth for the farmers in the county, who could then deposit their wealth in local banks. This wealth can then be redistributed to farmers in the form of loans, who can then use the access to finance to improve productivity further. That is, prosperous and productive farming counties are unlikely to appear in the low deposits group, creating a reverse causality.

We address this possibility by substituting the number of bank branches in a given county for the usual low deposits dummy variable as the measure of access to finance in our regressions. Although in the long run bank branches could migrate to where there is economic prosperity, in the short run changing local economic conditions surely have a relatively small impact on changes in the number of local bank branches. That is, the number of bank branches should be insensitive to changes in crop yields, but counties with more bank branches should be able to provide greater access to finance. Regression 5 in Table 7 reports the results of this regression.

Using number of bank branches as our measure of access to finance produces the same qualitative results as our low deposits dummy. We take the natural logarithm of one plus the number of branches and standardize the variable to be zero mean, unit variance. The coefficient on the triple interaction term is about 1.1, which means that a one standard deviation increase in the logged number of county-level bank branches explains more than one additional bushel of corn per acre when the demand for corn is high. In short, using number of bank branches produces the same qualitative results as using the low deposits quintile dummy variable.

6.2. Alternative methods of addressing endogeneity between access to finance and yields

We argue that in the short run the number of bank branches should be insensitive to changes in crop yields and, therefore, the number of bank branches provides a measure of access to finance that is relatively immune to reverse causality arguments that say finance follows productivity. However, there could be different views of what constitutes the short run. We further address the concern of endogeneity between access to finance and crop yields in this subsection.

We reproduce the results displayed in Panel A of Table 6 using an instrumental variables approach. We use as an instrument for the low deposits dummy variable the lagged value of the low deposits dummy variable. We instrument for both the interaction term and the direct effect. (We also separately instrument for the number of bank branches in a given county with the lagged number of bank branches in a given county, instrumenting for both the interaction term and the direct effect and find similar results.) In turn, we use values lagged one, two, and three years. These instruments satisfy the criteria of good instruments: the instruments are highly correlated with the explanatory variables (correlations for $Low\ Deposits_t \cdot Ethanol\ Period$ and $Low\ Deposits_{t-k} \cdot Ethanol\ Period$, $Low\ Deposits_t$ and $Low\ Deposits_{t-k}$, $Ln\ Branches_t \cdot Ethanol\ Period$ and $Ln\ Branches_{t-k} \cdot Ethanol\ Period$, and Ln $Branches_t$ and Ln $Branches_{t-k}$ are each above 0.900 and are statistically significant at the 1% level), the instruments are unlikely to be correlated with the error term in the second-stage regression equation because it is doubtful that current-year productivity can directly affect access to finance in the previous year, and the instruments should affect only productivity inasmuch as they affect access to finance in the current year. Access to finance measures are likely persistent, meaning a common component remains in each observation over time. This characteristic erodes the validity of the lagged measures of access to finance as instruments for current-year access to finance.

We find results similar to those of our baseline regressions, although the magnitudes are somewhat smaller. We find statistically significant negative coefficients on the instrumented low deposits dummy variable (coefficients range from -0.72 to -2.03, depending on which lag we use as an instrument) and positive and statistically significant coefficients on the instrumented number of bank branches in a given county (coefficients range from 0.29 to 0.52, depending on which lag we use as an instrument). (We do not tabulate these results.) In short, using an instrumental variables approach does not change our main conclusion—that access to finance enables productivity growth.

We also use an alternative instrument for access to finance: the number of senior citizens in a given county-year. Becker (2007) shows the intuitive result that metropolitan statistical areas with a large fraction of seniors have more bank deposits per capita. Unlike Becker (2007), however, we are interested in the level of bank deposits (i.e., deposits not scaled by population), so we use as an instrument the number of seniors in a given county-year instead of the fraction of seniors in a given county-year. We repeat the analyses in Panel A of Table 6 after conducting first-stage regressions in which we instrument for *Low Deposits* with the number of seniors in a given county-year, and we instrument for *Low Deposits* $\cdot$ *Ethanol Period* with the number of seniors in a given county-year interacted with *Ethanol Period*. The first-stage regressions pass Stock and Yogo (2005) *F*-tests, suggesting the instruments are valid. Although we do not report these results for the sake of conserving space, the second-stage results are in fact stronger and larger in magnitude than the results of our baseline tests.

As a concluding remark about reverse causality, we note that fluctuations in corn-based farm revenues do not seem to affect future bank deposits. We find that, for a typical county-year, total corn revenues (estimated by multiplying the average price of corn during the harvest period by production) are a minute percentage of bank deposits in that county. Further, deposits are insensitive to changes in corn revenues. The correlation between corn revenue and the following year's deposits is less than 1% and is statistically insignificant.

6.3. *Explanatory power of deposits in contiguous counties*

County-level bank deposits, our proxy for access to finance in the baseline regressions, might not be a reasonable measure of access to finance if financial capital is geographically mobile. County-level bank deposits could be capturing a wider, regional effect of access to finance, or capital markets perhaps are not sufficiently segmented for county-level bank deposits to proxy accurately for access to finance.

We address this possibility by examining whether access to finance in neighboring areas affects productivity. Specifically, we add to our regression a set of controls for whether the sum of bank deposits in all contiguous counties in our baseline regression framework is in the lowest quintile of the sum of bank deposits in all contiguous counties. (Using the average, not the sum, of contiguous county deposits, or using the level of deposits instead of the bottom-quintile dummy for the computation makes no difference.) We include the low-quintile contiguous county deposits dummy interacted with crop dummy variables and the ethanol boom period dummy, as in the baseline regression. Table 8 presents the results.

As expected, low-quintile contiguous counties' deposits do not explain own-county crop yields. The coefficients on the triple interaction terms involving low-quintile contiguous deposits are not significant for corn yields in any of the three regression specifications. Importantly, however, the triple interaction term involving own-county bank deposits remains negative and significant for corn. We interpret this result as evidence that county-level bank deposits are a reasonable measure of access to finance and that, consistent with Becker (2007), capital markets are geographically segmented.

6.4. *Access to finance and changes in planted acreage*

We examine planted acreage as an alternative proxy for productivity. In addition to trying to improve their per-acre output, corn farmers could respond to the ethanol shock by substituting corn acreage for other crops. We substitute planted acreage in a county for crop yields on the left-hand side of the baseline regression. Table 9 presents the regression results.

The relation in the baseline regressions—namely, that poor access to finance relates negatively to productivity—continues to hold. Specifically, we see that about three thousand acres of corn went unplanted in counties with bank deposits in the lowest quintile of the pooled average of county-year bank deposits, during the ethanol boom period.

6.5. *Tests using bank branching deregulation to measure access to finance*

Jayaratne and Strahan (1996) demonstrate that financial markets can directly affect economic growth. Their tests exploit the relaxation of bank branch restrictions in the United States. They show that rates of real per capita growth in income and output increased significantly in states after the state allowed intrastate bank branching.

We follow Jayaratne and Strahan's basic approach, and examine crop yields before and after states deregulated their banking systems by allowing mergers and acquisitions through the holding company structure. We use the Jayaratne and Strahan (1996) starting date, 1972, and extend the sample through 2002 (Jayaratne and Strahan's data end in 1992). We create a state-level dummy variable equal to one in the years following a state's bank branching deregulation and zero otherwise. Because this time period pre-dates the ethanol boom, we use a different demand shock for identification in our tests. In 1985, major US soft drink manufacturers Coca-Cola and PepsiCo switched the primary sweetener they used in sodas from sugar cane-based glucose to corn-based high fructose corn syrup. The availability of high fructose corn syrup in American foods jumped from 37.2 pounds per capita in 1984 to 45.2 pounds per capita in 1985. This one-year increase of 8.0 pounds per capita is the

Table 8

Regressions including deposits in contiguous counties. This table presents pooled ordinary least squares regression results based on county-year-crop observations. The dependent variable is crop yield, measured in bushels per acre. We separately winsorize corn and soybean yields at 1%. Regression 1 has no geographic fixed effects; Regression 2 includes state dummy variables; Regression 3 includes county-fixed effects. *Corn* is a dummy variable equal to one if the given yield is that of a corn crop and zero if the yield is that of a soybean crop. *Low Deposits* is a dummy variable equal to one if the level of bank deposits in a given county falls into the bottom quintile of all county-level bank deposits for a given year and zero otherwise. *Ethanol County* is a dummy variable equal to one if a given county has an ethanol production facility as of 2006 or has plans to build or expand ethanol production capacity as of 2006. *Ethanol Period* is an indicator variable equal to one if the yield is harvested during the ethanol boom period (2005 or later) and zero otherwise. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. *Precipitation* and *GDD* represent the inches of precipitation and number of growing degree days in an associated crop's region from May through October of a given year, respectively. The standard errors are in parentheses. They are robust to heteroskedasticity, and we cluster them at the county level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Independent variables	(1)	(2)	(3)
Corn · Low Deposits · Ethanol Period	−2.573*	−2.969**	−3.174**
	(1.533)	(1.515)	(1.594)
Corn · Low Contiguous Deposits · Ethanol Period	−0.800	−0.383	−0.430
	(1.927)	(1.889)	(1.915)
Corn · Low Deposits	−13.067***	−12.871***	−11.210***
	(2.040)	(2.024)	(2.058)
Corn · Low Contiguous Deposits	−2.138	−2.218	−3.592**
	(1.653)	(1.649)	(1.644)
Corn · Ethanol Period	2.037***	1.987***	1.740***
	(0.501)	(0.498)	(0.520)
Corn	94.953***	95.097***	96.054***
	(0.690)	(0.683)	(0.688)
Ethanol Period	4.647***	3.198***	0.359
	(0.505)	(0.427)	(0.711)
Ethanol County	8.615***	5.996***	–
	(1.516)	(1.244)	(–)
Low Deposits · Ethanol Period	−1.125**	−1.953***	−3.222
	(0.568)	(0.582)	(0.828)
Low Contiguous Deposits · Ethanol Period	0.217	−0.017	0.030
	(0.700)	(0.646)	(0.851)
Low Deposits	2.617**	6.600***	9.015***
	(1.166)	(1.154)	(1.816)
Low Contiguous Deposits	0.531	−0.031	3.440***
	(0.819)	(0.865)	(1.180)
Ln Population Density	2.821***	−0.979*	18.202**
	(0.548)	(0.502)	(7.434)
Unemployment	−1.689***	−1.513***	−0.426
	(0.298)	(0.264)	(0.281)
Per Capita Income	0.001	0.007***	0.003***
	(0.001)	(0.001)	(0.001)
Ln Precipitation	5.361***	2.096***	6.125***
	(0.753)	(0.615)	(0.420)
Ln GDD	4.860*	2.990	−7.371***
	(2.535)	(2.347)	(2.093)
Constant	−26.254	−1.821	−59.028
	(20.629)	(18.220)	(37.774)
N	12,849	12,849	12,849
Adjusted R^2	0.793	0.837	0.892
State dummies?	No	Yes	No
County fixed effects?	No	No	Yes

largest since the USDA began recording the availability of high fructose corn syrup for American consumption in 1966.

We capture this shift in demand for corn due to the widespread use of high fructose corn syrup with a dummy variable equal to one from 1985 (the year of the switch to high fructose corn syrup) on and zero in the previous years. We then repeat our productivity tests using state-level averages for crop yields, bank branch deregulation as a proxy for access to finance, and Coca-Cola and PepsiCo's switch to high fructose corn syrup representing a shift in demand for US corn. Standard errors are robust to heteroskedasticity and clustered at the state level, our unit of observation for these tests. Table 10 presents the results.

The results support both our findings mentioned above and the findings of Jayaratne and Strahan (1996). Corn yields increase by a statistically significant 22.3 bushels per acre in states with deregulated bank branching restrictions when the demand for corn is high because of Coca-Cola and PepsiCo's switch from sugar glucose to high fructose corn syrup as the primary sweetener in their soft drinks.

An important caveat is in order. We do not have weather data going back to this time period, so we do not control for temperature and precipitation as we do in our baseline tests. However, it seems unlikely that these

Table 9

Regressions with planted acreage proxying for productivity. This table presents pooled ordinary least squares regression results based on 12,849 county-year-crop observations. The regression specification *is Planted Acreage*$_{i,t,k}$=β_1 *Corn*$_k$ · *Low Deposits*$_{i,t}$ · *Ethanol Period*$_t$+β_2 *Corn*$_k$ · *Low Deposits*$_{i,t}$+β_3 *Corn*$_k$ · *Ethanol Period*$_t$+β_4 *Corn*$_k$+β_5 *Low Deposits*$_{i,t}$ · *Ethanol Period*$_t$+β_6 *Low Deposits*$_{i,t}$+β_7 *Ethanol Period*$_t$+*Controls*+*Constant*+$\varepsilon_{i,t,k}$. The dependent variable is planted acreage. Regression 1 includes no geographical dummy variables; Regression 2 includes state dummy variables; Regression 3 includes county fixed effects. *Corn* is a dummy variable equal to one if the given acreage is that of a corn crop and zero if the acreage is that of a soybean crop. *Low Deposits* is a dummy variable equal to one if the level of bank deposits in a given county falls into the bottom quintile of all county-level bank deposits for a given year and zero otherwise. *Ethanol County* is a dummy variable equal to one if a given county has an ethanol production facility as of 2006 or has plans to build or expand ethanol production capacity as of 2006. *Ethanol Period* is an indicator variable equal to one if the acreage is planted during the ethanol boom period and zero otherwise. We define the ethanol boom period as 2005 and later. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. *Precipitation* and *GDD* represent the inches of precipitation and number of growing degree days in an associated crop's region from May through October of a given year, respectively. The standard errors are in parentheses. They are robust to heteroskedasticity, and we cluster them at the county level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Independent variables	(1)	(2)	(3)
Corn · Low Deposits · Ethanol Period	−2,852**	−3,153**	−3,279***
	(1,388)	(1,311)	(1,108)
Corn · Low Deposits	133	843	3,430
	(2,905)	(2,872)	(2,911)
Corn · Ethanol Period	3,528***	3,443***	3,306***
	(552)	(512)	(437)
Corn	678	1,076	2,760*
	(1,463)	(1,454)	(1,481)
Low Deposits · Ethanol Period	−597	34	1,899**
	(1,504)	(1,398)	(924)
Low Deposits	−41,268***	−36,650***	−375
	(4,810)	(4,519)	(1,681)
Ethanol Period	−2,566**	−5,262***	−1,596***
	(1,263)	(1,131)	(354)
Ethanol County	40,835***	32,658***	–
	(5,172)	(4,394)	(–)
Ln Population Density	−5,507***	−6,230***	−20,868***
	(1,434)	(1,649)	(5,809)
Unemployment	−5,431***	−6,200***	86
	(832)	(779)	(97)
Per Capita Income	1.157***	1.013***	0.309***
	(0.356)	(0.344)	(0.113)
Ln Precipitation	6,069***	4,129**	−407**
	(1,874)	(1,893)	(161)
Ln GDD	−6,520	25,010***	−1,756***
	(6,230)	(7,516)	(610)
Constant	123,510**	−109,501*	162,646***
	(51,399)	(59,077)	(24,934)
N	12,849	12,849	12,849
Adjusted R^2	0.176	0.369	0.864
State dummies?	No	Yes	No
County fixed effects?	No	No	Yes

omitted variables are correlated with branching deregulation, so our coefficient estimates might not suffer from any severe bias.

6.6. Ethanol production capacity as a function of access to finance

So far we show that access to finance can affect productivity growth in response to a demand shock. We now ask whether access to finance has a direct effect on other economic outcomes. Specifically, we ask whether county-level financial development affects the location and size of ethanol plants. We perform a number of regressions involving ethanol production capacity as a function of access to finance. We have a snapshot of data for ethanol production capacity (in place and planned for future expansion or under construction) for 2006. We begin by regressing our dummy variable *Ethanol County* (a county that has an ethanol plant in place or planned for future expansion or under construction) on the low-quintile bank deposits dummy variable, the previous year's corn yield, and population density using a probit model. The second, third, and fourth regressions use the same regressors. However, for these regressions we use the following dependent variables: county-level ethanol production capacity in place, county-level ethanol production capacity planned for future expansion or under construction, and the sum of county-level ethanol production capacity in place with that planned for future expansion or under construction. Panel A of Table 11 presents the regression results.

We find a significant relation between ethanol production capacity and access to finance. In all four of our

Table 10
Productivity regressions with bank branch deregulation and corn syrup.
This table presents pooled ordinary least squares regression results based on 724 state-year-crop observations from 1972 to 2002. The dependent variable is average yield per acre. We separately winsorize corn and soybean yields at 1% and 99%. *Deregulation* represents a dummy variable equal to one in years following the allowance bank branching via merger and acquisition through the holding company structure and zero otherwise. *Corn Syrup* represents a dummy variable equal to one in the years following Coca-Cola and PepsiCo's transition from sugar glucose to high fructose corn syrup and zero otherwise. Coca-Cola and PepsiCo switched to corn syrup in 1985. The standard errors are in parentheses. They are robust to heteroskedasticity. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Independent variables	Average yield (bushels)
Corn · Deregulation · Corn Syrup	22.260*
	(11.479)
Corn · Deregulation	−21.575
	(12.436)
Corn · Corn Syrup	17.755***
	(2.936)
Corn	63.909***
	(3.461)
Deregulation · Corn Syrup	−10.065*
	(5.158)
Deregulation	11.637*
	(5.383)
Corn Syrup	3.208*
	(1.757)
Constant	42.949***
	(1.757)
N	724
Adjusted R^2	0.934
Year dummies?	Yes
State dummies?	Yes

regression specifications we find a significant and negative effect of poor access to finance on ethanol plant location or size. (We find similar results when we use the number of county-level bank branches as the explanatory variable, instead of the low-deposits dummy.) Thus, we provide some support for the idea that finance is related to economic growth and viability by virtue of the ethanol plants built in finance-heavy counties.

An important caveat to the results above is that the location or capacity of ethanol production plants, or both, could be endogenous. Plants' location or size could be chosen based on where access to finance is good, or finance could follow to the areas where ethanol plants are. We address this point by instrumenting for access to finance in 2006 with access to finance in 2004 (the year prior to the ethanol mandates) and using the instrumented measure of access to finance to explain ethanol production capacity under construction or planned for expansion as of 2006. These instruments satisfy the criteria of good instruments: the instruments are highly correlated with the explanatory variables (correlations for $Low\ Deposits_{2004}$ and $Low\ Deposits_{2006}$ and for $Ln\ Branches_{2004}$ and $Ln\ Branches_{2006}$ are statistically significant at the 1% level), the instruments are unlikely to be correlated with the error term in the second-stage regression equation because it is doubtful that future ethanol production capacity as of 2006 can directly affect access to finance in 2004, and the instruments should affect only future ethanol production capacity inasmuch as they affect access to finance in the 2006.

We use two measures of access to finance: the low-quintile deposits dummy variable and the number of bank branches in a given county. Panel B of Table 10 presents the regression results. Our results indicate that the exogenous portion of access to finance explains future ethanol production capacity for each measure. For instance, if a county is in the low-deposits quintile, it will on average forgo the opportunity to host over 1.3 million gallons of ethanol production capacity in each of the following years. (The regression coefficient is -0.300, and $e^{0.300}$ is about 1.35.) Similarly, for each standard deviation more bank branches that a county has, it can expect to host an additional 1.2 million gallons of ethanol production capacity in each of the following years. (The regression coefficient is 0.156, and $e^{0.156}$ is about 1.2.) These results provide a tangible example of how access to finance can lead to considerable improvement in economic outcomes.

6.7. *Crop prices as an alternative proxy for demand*

As an alternative to our ethanol period dummy, we use spot market prices for our commodities as a proxy for demand for the crops. Price is not an ideal proxy for demand because changes in price could reflect changes in demand or supply. A visual inspection of a time series of crop prices plotted in Fig. 6 shows a large spike in price for soybeans in late 2004. This price spike was due to supply shocks in the United States and Brazil, the world's two largest soybean producers.[5] Even though price changes could be due to supply or demand changes, we nonetheless proceed with this robustness test using price as an admittedly imperfect proxy for demand shifts.

Spot market price data are collected from Bloomberg. In particular, we average the daily spot market prices from September through October (i.e., spot market prices around the time of harvest) for corn and soybeans to proxy for the demand for each crop during a given year. This variable enters our multivariate regressions. Fig. 6 displays spot market prices over time.

We use pricing data from spot markets in Illinois. (The choice of the spot market from which we select the pricing data makes little difference in our tests. For example, the price of yellow-kernelled corn harvested in the USDA Northern Illinois region has a correlation of 0.973 with that harvested in the USDA Northeast Iowa region.) We substitute crop prices for the ethanol period dummy throughout the baseline regression equation, including the interaction terms, and add year dummies. We find qualitatively similar results to our main tests. We find corn yields are lowest in counties with poor access to finance (i.e., the counties have bank deposits in the lowest quintile), yet particularly so when the demand for corn is high (i.e., the price of corn is high) due to increasing interest in ethanol.

[5] Source: Bruce A. Babcock, Iowa State University, Center for Agricultural and Rural development (http://www.extension.iastate.edu/AGDM/articles/babcock/BabMay04.html).

Table 11
Ethanol production as a function of access to finance. Panel A presents regression results based on 911 county-level observations for 2006. Regression 1 is a probit regression in which the dependent variable is a dummy variable equal to one if a given county has an ethanol plant as of 2006 or has an ethanol plant under construction or planned for expansion. Regressions 2 through 4 are ordinary least squares regressions. The dependent variable of Regression 2 is the log of a given county's ethanol production capacity in place as of 2006. The dependent variable of Regression 3 is the log of a given county's ethanol production capacity under construction or planned for expansion as of 2006. The dependent variable of Regression 4 is the log of the sum of a given county's ethanol production capacity in place as of 2006 and ethanol production capacity under construction or planned for expansion as of 2006. *Low Deposits* is a dummy variable equal to one if the level of bank deposits in a given county falls into the bottom quintile of all county-level bank deposits for a given year and zero otherwise. *Corn Yield*$_{t-1}$ represents a given county's corn yield in 2005. *Population Density* is equal to the county population for 2006 divided by the number of square miles in the county. The standard errors are in parentheses. They are robust to heteroskedasticity. Panel B presents regression results based on 903 county-level observations for 2006. The dependent variable for each regression is the log of a given county's ethanol production capacity under construction or planned for expansion as of 2006. We instrument for access to finance in two ways and then use the instrumented values to explain the dependent variable. In Regression 1 we instrument for the low deposits dummy variable as of 2006 with the low deposits dummy variable as of 2004. In Regression 2 we instrument for the standardized natural log of the number of bank branches in a given county as of 2006 with the standardized natural log of the number of bank branches in a given county as of 2004. *Corn Yield*$_{t-1}$ represents a given county's corn yield in 2005. *Population Density* is equal to the county population for 2006 divided by the number of square miles in the county. *Unemployment* is equal to the percentage of the working population without employment for a given county-year. *Per Capita Income* is the average personal income for a given county-year, measured in thousands of dollars per person. The standard errors are in parentheses. They are robust to heteroskedasticity. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Independent variables	Dependent variable			
	Ethanol county dummy (1)	Ln(Production capacity in place) (2)	Ln(Planned capacity) (3)	Ln(Planned plus in-place capacity) (4)
Panel A: Ethanol regressed on low deposits dummy variable				
Low Deposits	−0.826***	−0.292***	−0.230***	−0.501***
	(0.232)	(0.090)	(0.088)	(0.120)
Corn Yield$_{t-1}$	0.009***	0.003***	0.005***	0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Population Density	−0.106*	−0.047	−0.037	−0.080*
	(0.061)	(0.033)	(0.027)	(0.041)
Unemployment	−0.118**	−0.054**	−0.033	−0.077**
	(0.060)	(0.023)	(0.027)	(0.033)
Per Capita Income	2.030×10^{-5}	1.060×10^{-5}	5.120×10^{-6}	1.280×10^{-5}
	(1.550×10^{-5})	(7.640×10^{-6})	(8.330×10^{-6})	(1.050×10^{-5})
Constant	−2.025***	0.004	−0.171	−0.083
	(0.610)	(0.277)	(0.308)	(0.387)
N	911	911	911	911
Pseudo- or adjusted R^2	0.097	0.036	0.033	0.063

Independent variables	(1)	(2)
Panel B – Future ethanol production capacity regressed on instrumented access to finance		
Instrumented Low Deposits Dummy	−0.300**	
	(0.128)	
Instrumented Ln(Number of Bank Branches)		0.156*
		(0.084)
Corn Yield$_{t-1}$	0.005***	0.005***
	(0.001)	(0.001)
Population Density	−0.049	−0.092
	(0.038)	(0.060)
Unemployment	−0.032	−0.027
	(0.032)	(0.033)
Per Capita Income	6.010×10^{-6}	-8.820×10^{-7}
	(9.870×10^{-6})	(9.990×10^{-6})
Constant	−0.127	0.093
	(0.361)	(0.419)
N	903	903
Adjusted R^2	0.027	0.027

6.8. Regressions on subsamples sorted by farm size

The NASS provides data on the average number of acres per farm, per county-year for several states, including four states in our sample: Iowa, Nebraska, Ohio, and Wisconsin. We use this measure as a county-level proxy for typical farm sizes in the county. We partition our sample for these four states into two groups based on the average number of acres per farm, and we run the baseline regressions from Table 6 separately on both subsamples. (Because the farm size measure imposes a large and possibly nonrandom reduction in our sample size, we do not tabulate these results.)

We find that the finance-causes-growth effect is significant for small-farm counties, but not for large-farm counties. This intuitive result suggests that the investment decisions of

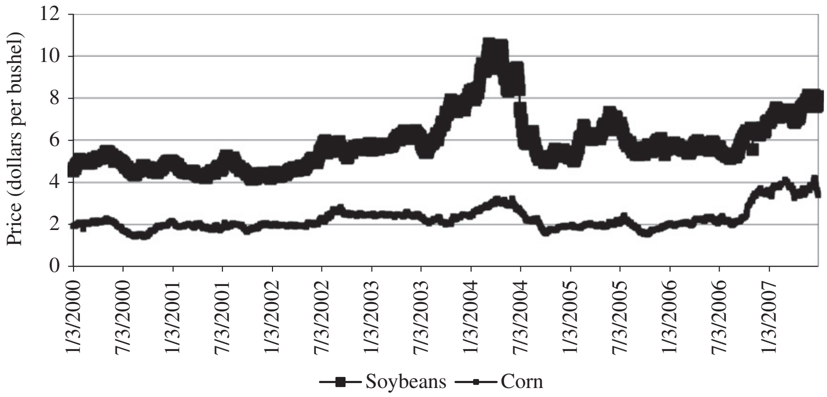

Fig. 6. Crop prices over time. This figure displays daily prices of yellow soybeans and yellow-kernelled corn sold on spot markets in Illinois from January 2000 to June 2007 in dollars per bushel.

smaller firms (farms) are more sensitive to access to external finance than larger firms (farms). Other partitions—by quartile or decile, for instance—give the same results.

6.9. Alternative productivity controls

Our baseline regressions in Table 7 use soybeans yields as a control. The purpose of including soybeans yields and creating a triple interaction term is to test whether increases in corn productivity are unique to corn, the crop we argue has recently experienced a demand shock. To establish the robustness of our results, we also use two other productivity benchmarks: national labor productivity growth in the business sector and the average of national soybean and wheat productivity (the two largest cash crops in the US behind corn). Data on labor productivity come from the Bureau of Labor Statistics and data on agricultural productivity come from the NASS.

Instead of a triple-interaction term, we regress corn yields on access to finance interacted with the ethanol period dummy variable, and we include either national labor productivity or overall agricultural productivity as a separate explanatory variable. In other words, we repeat the corn-only regressions in Table 6, but with national labor productivity or the average of national soybean and wheat productivity as a control variable. Our results are unchanged. Corn yields are higher in counties with good access to finance during the ethanol period, even after controlling for other productivity benchmarks.

6.10. Regressions with only counties that do not change treatment status

In our sample some counties switch from the low-deposit quintile to a higher-deposit quintile (or vice versa) during the sample period. Specifically, 93 of our Midwestern counties do not maintain a constant position in either the low-deposit quintile or higher-deposit quintile throughout the sample period. These switching counties do not meet the requirement that our control and treatment groups be identified before the ethanol shock and independent of the ethanol shock.[6] We repeat all of the regression analysis described in the sections above, excluding observations coming from these counties. Excluding these observations strengthens our findings. In untabulated results, the coefficients of interest grow slightly in economic magnitude and gain statistical significance when we restrict our sample to counties with a constant position in either the low-deposit quintile or a higher-deposit quintile. For example, the coefficient on the triple interaction term in Table 7, Regressions 1, 2, and 3 changes from -2.72 to -3.34, -3.00 to -3.47, and -2.90 to -3.23, respectively.

7. Conclusion

This paper examines the effect of access to finance on productivity. We exploit an exogenous shift in demand for US corn to expose county-level productivity responses in the presence of varying levels of access to finance.

The exogenous shift in demand for corn is due to a boom in ethanol production, which is a result of a number of complementary forces (rising crude oil prices, the Energy Policy Act of 2005, and new federal tax incentives). We find that counties in the midwestern United States with the lowest levels of bank deposits have been unable to increase their corn yields as much as other counties. This result demonstrates the positive impact of access to finance on productivity.

We employ a differences-in-differences-in-differences testing approach. Using soybeans as a control crop, we find that the increase of corn yields in counties with high levels of bank deposits is greater over our sample period than in counties with low levels of bank deposits, even in comparison with the yields of soybeans. Specifically, counties with high levels of bank deposits increased their corn yields by 10.4 bushels per acre (10.4 bushels per acre is approximately half of a standard deviation of an average county's annual corn yield per acre) more than counties with low levels of bank deposits over the sample period. In contrast, we find no significant difference between the increases of soybean yields

[6] We thank the referee for this point.

in counties with high and low levels of bank deposits over the sample period. This result eliminates the concern that we are simply capturing overall growth in agricultural productivity.

We augment the differences-in-differences-in-differences test with pooled OLS regressions. We regress crop yields on crop dummy variables, a dummy variable measuring low access to finance, proxies for the demand for corn, variables capturing meteorological conditions, and a host of interaction terms. We find that corn yields have increased in response to the exogenous shift in demand for corn, but particularly so in counties associated with strong access to finance. Said differently, corn yields in counties with poor access to finance have been particularly lower than those in counties with high access to finance following the exogenous shift in demand for corn. Specifically, our main regressions show that corn yields were about 2.7 to 2.9 bushels per acre lower in counties with bank deposits in the lowest quintile during the ethanol boom period. This magnitude is greater than 10% of a standard deviation of an average county's annual corn yield per acre. This result is consistent with that of the differences-in-differences-in-differences test, and further confirms the positive relation between access to finance and productivity.

Our findings show a crucial linkage between finance and economic growth. Many economists believe in a positive relation between finance and economic growth. However, the specific channels through which this relation operates are less clear. Our findings provide concrete evidence that increased productivity is a key channel through which finance causes economic growth.

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